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Job Hopping, Earnings Dynamics, and Industrial Agglomeration*

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This paper investigates the implications of industrial clustering for labor mobility and earnings dynamics by taking advantage of new employee-employer matched micro-data from the U.S. Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) Program. Motivated by a theoretical model in which geographically clustered firms compete for workers, I exploit establishment-level variation in agglomeration to explore the impact of clustering in the prepackaged software industry on labor market outcomes. The results show that clustering makes it easier for workers to job hop among establishments within the sector. Further, workers in clusters have relatively steep earnings-tenure profiles, accepting lower wages early in their careers in exchange for stronger earnings growth and higher wages later. These findings underscore the importance of geography in understanding labor market dynamics within industries and highlight the role of clustering among high-technology firms in promoting job and earnings mobility.

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1 Introduction

Agglomeration is a conspicuous feature of the economic landscape. Three-fourths of Americans live in cities that account for less than 2% of the land area in the Lower 48 (Rosenthal and Strange 2003), and only 4% of total acreage in the contiguous states is considered large urban or built-up (U.S. Department of Agriculture 2001). Not only is economic activity heavily concentrated in urban areas, but evidence also suggests that regions tend to specialize in certain industries, with firms in a number of sectors concentrating in particular locations to an extent over and above what we would expect given the distribution of economic activity more generally (Porter 1990; Krugman 1991; Kim 1995; and Ellison and Glaeser 1997, 1999).

Both by facilitating the pooling of skilled labor and by fostering competition over workers, geographic clustering by firms in different industries could influence local labor market dynamics. Variation in worker and job flows across regions as well as within narrowly defined sectors is well documented, but not well understood (Eberts and Montgomery 1995, Davis and Haltiwanger 1996, Dumais et al. 2002, Faberman 2003). Employing new data and novel measures of concentration, this paper examines the nature and extent of industrial clustering and explores how agglomeration among establishments in one high-technology sector interacts with labor mobility, earnings levels, and earnings growth rates. To explain how variation in labor market outcomes across clustered and dispersed establishments could stem from the strategic interaction of firms that weigh the benefits and costs of agglomerating, and in particular the benefits of having access to a pool of skilled workers and the costs of having to compete over them, I develop a model of on-the-job search that features a spatial dimension and incorporates industry-specific skills.

Consistent with the model, an empirical analysis using rich longitudinal employee-employer matched data reveals that geographic clustering among establishments in the prepackaged software industry is associated with abbreviated job durations and greater job-hopping among individuals within the sector. Moreover, relative to those employed by firms in more remote locations, workers in regions with greater

clustering generally enjoy robust within-job earnings growth. However, workers reap these higher returns to tenure in clusters only after making implicit investments through lower wages early in their careers. These findings underscore the importance of geography in understanding labor market dynamics within industries and highlight the role of clustering among high-technology firms in promoting job hopping and earnings mobility.

The paper proceeds as follows. The next section reviews the literature on industrial clustering, labor pooling, and job and earnings mobility. Section 3 develops a theoretical model to motivate my analysis of industrial agglomeration and local labor market dynamics. Section 4 describes the data I use in this study and the methodology I employ to measure clustering and to examine patterns of agglomeration. After Section 5 presents descriptive statistics, Section 6 turns to the empirical analysis. Section 7 concludes.

2 Literature

Since Alfred Marshall's observations on the geographic concentration of certain trades and manufacturing activities in his 1890 *Principles of Economics*, a substantial amount of evidence has accumulated on the degree of industrial agglomeration. The leading theoretical rationales for clustering among firms within industries are essentially the same now as when Marshall first proposed them over a century ago. These explanations include access to intermediate or final product markets, technological spillovers, and labor pooling.[1] Though each explanation has some degree of substantiating evidence and all are likely at work to varying degrees in most industries,[2] this paper will focus on the labor market as

[1] For models centered on the notion that firms co-locate to economize on transport costs and exploit access to product markets, see Ethier (1982), Krugman (1991), and Fujita et al. (1999). For technological spillover models, or models that focus on externalities arising when some firms benefit from others' R&D without sharing in the costs, see Fujita and Ogawa (1982), Jovanovic and Rob (1989), Jovanovic and Nyarko (1995), and Glaeser (1999). For labor pooling models, or models that highlight the potential role of sorting and matching effects and/or risk pooling in giving rise to agglomeration, see Salop (1979), Kim (1990, 1991), Helsley and Strange (1990), and Duranton and Puga (2004).

[2] For evidence that firms cluster to economize on transport costs and exploit product markets, see Krugman (1991), Justman (1994), Holmes (1999), and Davis and Weinstein (1999). See Jaffe et al. (1993) and Audretsch and Feldman (1996) for empirical work using patent citations to measure technological spillovers. For evidence that

the as the source of incentives for firms to cluster or disperse, formulating a model in which competition over skilled workers plays a critical role and testing the theory's implications on an industry in which labor market considerations likely take center stage in determining the spatial distribution of firms.

Labor pooling, or the accumulation of individuals with specific skills in an area in which an agglomeration of firms exists, is typically perceived as a means to ensure that employers can find workers with needed characteristics and that workers can find jobs that match their skills (Helsley and Strange 1990, Costa and Kahn 2000, Wheeler 2001). Clustering in a particular industry can encourage workers to specialize by reducing the risk associated with making industry-specific human capital investments (Rosen 1972, Pakes and Nitzan 1983, David and Rosenbloom 1990, Rotemberg and Saloner 2000). Overall, by lowering search costs for firms and workers and by improving match quality, labor pooling is generally assumed to provide strong incentives for firms in some industries to cluster.

One strand of literature, building on Arrow's (1962) idea that the knowledge of a firm is embodied in its workers, emphasizes a potential link between labor pooling and technological spillovers. Labor mobility, or the movement of workers between establishments in a given area, could facilitate productivity-enhancing knowledge transfers (Almeida and Kogut 1999, Combes and Duranton 2006, Fallick et al. 2005, Møen 2005). However, clustering in an effort to draw on a pool of skilled labor could come with a cost: a firm that locates close to others in the same industry faces a heightened risk that nearby firms will poach its experienced employees.[3] Firms could lure employees from other businesses by offering superior earnings prospects, although threatened firms could also counter potential poaching by raising wages for their own workers. Hence, in sectors in which industry-specific human capital is important, there exists a tradeoff to clustering that is intimately tied to labor mobility (Combes and Duranton 2006).

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labor market considerations are important determinants of business location in some industries, see Costa and Kahn (2001), Rosenthal and Strange (2001), Dumais et al. (2002), and Andersson et al. (2006).

[3] Clustering clearly opens the door to greater local product market competition and congestion effects. Yet agglomeration in a particular industry can also have its advantages on the product market side; clustering could be associated, for example, with gaining access to upstream and downstream producers and consumers (Holmes 1999). Firms must weigh these factors, in addition to the labor market factors spelled out in more detail in the text (which undoubtedly have knock-on effects in the product market), in their location decisions.

3 Model

To motivate the subsequent analysis, I briefly outline in this section a theoretical model of on-the-job search that highlights the tension between labor pooling and poaching by considering the strategic interaction of firms as they compete over labor. The model, which I describe in greater detail in Appendix 1, can account for several empirical regularities, including that clustering among high-technology establishments that value industry-specific skills is associated with shorter job durations and more job-hopping by workers. Consistent with the data, the model also predicts that workers in high-technology industry clusters will accept wage discounts at the start of their careers, but that they can expect faster wage growth and higher long-run earnings compared to those employed outside clusters.

The model adds to the on-the-job search models pioneered by Burdett and Mortensen (1998) and extended by Postel-Vinay and Robin (2002) by incorporating a spatial dimension and industry-specific skills. Firms in a high-technology industry have the option of clustering, in which case they can tap into a pool of skilled labor but also face the risk of having their employees lured away by firms that can offer more attractive earnings prospects, or dispersing, in which case they do not have access to skilled workers but also face no risk that their employees will be poached by other firms. Operating in an environment of perfect information, firms pay each of their workers no more than that which is required to prevent them from quitting for another job. However, given heterogeneous firm productivity, workers in a cluster may experience both within-job wage changes, which arise as firms raise their employees' wages to counter offers from other firms located nearby, and between-job wage changes, which arise as firms make sufficiently attractive offers to draw workers from their current employers.

3.1 Setup

There exist two industries, one of which is comprised of low-technology firms (L) and one of which is comprised of high-technology firms (H). Homogenous and perfectly competitive L-industry firms pay

all workers their constant marginal product b and exist in each and every one of an infinite number of locations. Firms in the H industry, of which there is a fixed number N^W in the world, have constant returns to labor but are heterogeneous in their productivity p, which has CDF F over $[p_{min}, p_{max}]$.[4] I assume for simplicity that each H-type firm's p is time invariant and that $p_{min} = b$. H-type firms, which unlike firms in the L industry value industry-specific experience, may locate in a pre-existing cluster, of which I assume there exists at most one, or in any one of an infinite number of isolated regions. Only one H-type firm can locate in an isolated region.

There is a working population of fixed size M in all locations, and workers, while free to move between jobs within a region, cannot move among regions.[5] Workers have a discount rate $\rho > 0$ and linear flow utility $u(x) = x$. All workers in a cluster of H-type firms are assumed to hold industry-specific skills that serve to save each agglomerated employer a recurring cost c that otherwise affects productivity additively; that is, whereas a firm with productivity p in a cluster earns profits on a given worker of p less the wage it pays to that worker, a firm with productivity p outside a cluster earns profits on a given worker of p-c less the wage it pays to that worker.[6] This productivity differential in favor of workers in

[4] A fixed number of total H-type firms could arise due to demand-side factors in the industry.

[5] Although the geographic immobility of workers represents a strong assumption, this paper aims to explain localized job flows and earnings dynamics conditional on the spatial distribution of economic activity. The assumption turns out only to be relevant to obtaining the model's main results to the extent that workers cannot have the option of relocating to the clustered region from an unclustered one and vice versa; workers will have no incentive to move between unclustered regions. Furthermore, evidence suggests that even in high-technology sectors, the geographic mobility of individuals is limited and much job-hopping occurs within quite confined areas. According to Census data, in the information industry (NAICS 51), 19% of employed civilians 16 years of age and over changed residence addresses between 2004 and 2005; 56% of these movers stayed within the same county and 80% within the same Census division (http://www.census.gov/population/www/socdemo/migrate.html). Among individuals in my sample who leave one job within the specific four-digit high-technology industry I consider (NAICS 5112) for another in the same industry (and including only those for whom we have accurate home address information and whose calculated commuting distances are less than 100 miles), the average physical distance between employers for whom they work is 16.6 miles and for over half of job hoppers it is less than 12 miles. Moreover, commuting distances for in-state workers in the industry tend to change little as individuals job hop; the average distance between home and work stretches from about 16.9 miles to 18.4 miles with job changes within the sector.

[6] An alternative way to model the difference between workers inside and outside a cluster is to assume that all workers inside the cluster have past experience in the industry whereas workers outside the cluster do not. In that case, H-type firms that disperse might have to bear a one-time training cost on each worker they hire. As we analyze only steady state conditions, this changes only the form in which any productivity discount or cost enters the profit equation for isolated firms and not the main results or predictions of the model.

clusters could stem from their increased exposure to the industry, social networking, or any other form of endowment or spillover than might give rise to geographic variation in industry workforce quality.[7]

H-type firms make take-it-or-leave-it offers to workers in each location. L-industry workers receive offers from firms in the H-industry at a rate λ and H-industry workers receive offers from H-type firms in a region at a rate γ. Wages in a given job in the H industry can be renegotiated only by mutual agreement between the firm and the worker, which implies that while workers can receive pay raises within a firm, they cannot receive pay cuts. For simplicity, we assume a random matching technology such that workers in both the L industry and the H industry receive offers from each and every H firm with equal probability. Let $w'_0(p)$ denote the wage an H-type firm with productivity p must offer to attract a worker from industry L, and let $w'(x, y)$ denote the wage required for an H-type firm with productivity y to attract a worker from an H-type with productivity $x < y$. In all locations, H-industry workers are separated from their jobs at an exogenous rate δ, in which case they immediately obtain jobs in the L industry.

3.2 Labor Market Conditions Inside an Industry Cluster

A worker in the L industry in a cluster of H-type firms will accept any offer from an H-type that promises more in present value terms than earning b forever. When a worker earning a wage w at an H-type firm with productivity p in a cluster receives an offer from a "rival" H firm with productivity p^r, the two firms make competing wage offers to the worker under Bertrand competition. The more productive firm will ultimately win the worker since the productivity of the less productive firm places an upper bound on how much it would be willing to pay to retain or poach him or her.

Hence, when an H-type firm meets a worker employed by another H-type firm, there are three possible outcomes. Let $q(w, p)$ denote the threshold level of marginal productivity above which an H-type firm contacting a worker earning w in another H-type firm with productivity p induces a wage increase

[7] Such a productivity advantage in industries in which input-output linkages might be relatively important could stem from reduced transportation costs or improved access to consumer markets.

for the worker in that firm (where $q(w, p) \leq p$). When a worker at an H-type firm encounters another H-type firm, therefore, one possibility is that $p^r \leq q(w, p)$, in which case the worker's wage and employment status will not change as a result of the meeting. In this case, the rival firm cannot profitably offer the worker a wage that the worker would find acceptable given his current employment situation. A second possibility is that $q(w, p) < p^r \leq p$, in which case the worker's current wage is less than the wage that would make him or her indifferent between working at the two employers. In this case, since the productivity of each firm places an upper bound on how much it would be willing to pay to employ the worker and $p^r \leq p$, the worker's wage will be bid up within his or her current firm to $w'(p^r, p)$, precisely the level that renders that worker indifferent between staying with his or her employer and hopping to the rival firm. That is, the worker receives a "promotion" to a wage equivalent to that which would be required for the incumbent firm to lure the worker away from the rival were he or she to be employed there. If p^r is strictly less than p, the wage resulting from the competition will be less than p^r, since, with its higher productivity level, the worker's current employer offers superior long-term earnings prospects than does the rival firm.[8] Finally, if $p < p^r$, the challenging firm can successfully lure the worker away from his current employer, as the rival can extend a more attractive wage offer and still profitably employ the worker. In this case, given the nature of competition, the rival firm will only offer the minimum wage required to poach the worker, or the wage $w'(p, p^r)$ such that the worker is indifferent between working at the two competing firms.

Importantly, a worker's wage need not be bid all the way up to the productivity level of the "loser" of the competition, as the worker is willing to accept a lower wage to work at a higher productivity firm that can offer superior long-term earnings prospects. When faced with competition over scarce labor, a more productive firm has the ability to grant greater future wage increases and hence provides more favorable career earnings prospects. Therefore, in anticipation of higher future earnings, workers, and in particular

[8] If $p^r = p$, the worker's wage will be bid up to exactly the productivity level of the two competing firms and I assume that the worker remains with his or her current employer.

those at the top end of the wage distribution at low productivity firms, will be willing under some circumstances to accept wage cuts to move to better firms.

Leaving the derivation to Appendix 1, the optimal wage that an H-type with productivity p^r offers to a worker earning w at a firm with productivity $p < p^r$ is

$$w'(p, p^r) = p - \gamma/(\rho + \delta)\int_p^{p^r}[1 - F(x)]dx$$

This expression yields several insights. First, $w'(p, p^r)$ does not depend on the current wage w, though it does depend critically on the current employer's productivity p. This is not surprising given that a firm extending an offer cares not what the worker is currently earning but rather only the maximum that the current firm could offer and that the worker would accept. Also, the threshold wage required to attract a worker at an H-type firm with productivity p is, in fact, less than p. The amount by which it is less than p reflects the option value of working at the higher productivity firm, and that value increases with the difference between the productivities of the two employers. Indeed, a poacher's offer can be lower the greater is p^r and the lower is p, and in some cases, depending on his or her wage history within a firm, a worker might accept a wage cut to move to an employer in which he or she expects stronger wage growth. Lastly, the higher the arrival rate or the lower the exogenous separation rate, the lower the wage offer required to poach a given employee.

We can derive a similar equation for the offer made to a worker in the L industry who is earning b (again, see Appendix 1 for details).

$$w'_0(p) = b - \gamma/(\rho + \delta)\int_b^{p}[1 - F(x)]dx$$

Intuitively, an H-type firm can pay less than b to attract a worker from the L industry. In this case, the prospect of higher future wages as a worker moves up the wage distribution induces him or her to accept

a temporary pay cut to escape from the L sector; in a sense, a worker is willing to "pay" to get his or her foot in the door of the H industry. Further, the greater its productivity, the less an H-type firm must offer to hire a worker from the L industry. Meanwhile, a higher arrival rate and a lower exogenous separation rate drive down the wage offer required to attract a new employee from the L industry. Notably, $w'_0(p)$ does not depend on λ since, unlike in standard search theory where an extended search duration may improve the value of the job that a worker ultimately accepts, rejecting an offer from an H-type firm never pays off in this model.

3.3 Labor Market Conditions Outside an Industry Cluster

An H-type firm that locates in one of the infinite number of isolated regions does not have to compete with other H-type firms over workers, but must bear a recurring cost associated with distancing itself from similar firms. As in the cluster, in an isolated region, an H-type firm that meets a worker in the L industry will make the lowest possible wage offer to hire the worker. That offer must provide a value equal to the opportunity cost of employment in industry L. Unlike in the industry cluster, though, the lack of other H-type firms with which to compete over workers in a remote location implies $\gamma = 0$. Therefore, as I describe more formally in Appendix 1, an isolated H-type firm need only pay its workers the going market wage in the L industry (that is, $w'_0(p) = b$ for all $p \in [p_{min}, p_{max}]$); wages are never bid upward due to competition and the utility workers derive from working in the L and H industries are equalized. Ultimately, then, workers in an unclustered area are indifferent between working at the sole H-type firm and working in the L industry, and an H-type firm that distances itself from other firms in the same industry need never pay a given worker more than what is required to attract him or her from the L industry.

3.4 The Spatial Distribution of Firms

To gain insight into the model's implications for the location decisions of firms in the H industry, we turn to derivations of equilibrium conditions. As I show in Appendix 1, we can derive steady state profits for an H-type firm with productivity p in a cluster of N H-type firms, denoted $\pi^c(p)$, as

$$\pi^c(p) = \{[(\delta+\gamma)\lambda\delta M]/[(\delta + \lambda)(\rho + \delta)N]\} \int_b^p [\{\rho + \delta + \gamma[1 - F(x)]\} / \{\delta + \gamma[1 - F(x)]\}^2]dx$$

and steady state profits for an H-type firm with productivity p outside the cluster, $\pi^u(p)$, as

$$\pi^u(p) = [(p - c - b)\lambda M]/(\delta + \lambda)$$

An H-type with a given p compares steady state $\pi^c(p)$ and $\pi^u(p)$ and determines, taking N as given, whether to cluster. In equilibrium, those firms that cluster have productivities such that $\pi^c(p) > \pi^u(p)$; as discussed in Appendix 1, we have in mind reasonable conditions under which several possible equilibriums could arise, including extreme cases in which all high-technology firms cluster or disperse as well as intermediate cases in which some firms cluster, some disperse, and none has an incentive to deviate.

3.5 Job Hopping and Earnings Dynamics Inside and Outside an Industry Cluster

While the model has implications for firm location decisions, this paper aims to analyze clustering's consequences with respect to worker job mobility and earnings dynamics. Hence, positing that there exists an equilibrium in which some firms cluster and others disperse, I concentrate on the empirical implications of the model that are independent of the determination of the spatial distribution of firms. Conditional on the existence of an equilibrium in which firms make heterogeneous location choices (an assumption that finds support in the data even within very narrowly defined industries), the model

generates several testable predictions regarding labor market dynamics inside and outside an industry cluster.

Prediction 1: **Due to on-the-job search and labor poaching, job durations will be shorter inside a cluster than outside a cluster.**

A worker in the H industry outside a cluster separates from a job with an H-type firm with productivity p only at the exogenously given separation rate, whereas a worker in a cluster separates from a job with a firm with productivity $p < p_{max}$ at the separation rate plus the probability of being contacted by another H-type firm with productivity greater than p. The likelihood of exiting a clustered H-type establishment is decreasing in the productivity of an individual's current employer and increasing in the arrival rate of offers from the H industry.

A related prediction of the model concerns the probability that workers move between jobs at firms within the H industry.

Prediction 2: **Job-hopping within an industry will be more prevalent inside a cluster than outside a cluster.**

In an area in which only one H-type firm operates, given the immobility of workers across locations in the model, the likelihood that an individual will transition directly from one H industry job to another H industry job is zero. In agglomerated areas, though, the probability that a worker employed at a firm with productivity p will transition to another firm equals $\gamma[1 - F(p)]$, which is greater than zero if $p < p_{max}$. A worker's willingness to job hop within the sector depends on whether the prospective employer can promise larger wage gains over the long run than the current employer. Though the model assumes for tractability a constant arrival rate γ within a cluster, to the extent that a greater concentration of firms would increase the rate at which workers receive offers in reality, greater clustering would drive up the probability of a within-industry transition for a worker at any given establishment.

An H-type firm that meets a worker in the L industry need only offer that worker a wage that makes him or her indifferent between taking the job and continuing to work in the L industry. In general, this

wage is lower in clusters of H-type firms, where a job in the H industry, in contrast to one in the L industry, offers opportunities for advancement.

Prediction 3: **Inside a cluster, workers transitioning into the industry will accept a drop in earnings, whereas workers outside a cluster will not.**

The prospect of higher future wages due to competition among firms in an agglomerated area can induce a worker to accept a pay cut to enter the H industry. In an area that is not agglomerated, however, there is little incentive for workers to make such an implicit investment since there is no possibility of reaping any returns on it in the long run. As above, to the extent that greater concentration might increase the arrival rate, more clustering would increase the size of the initial pay cut that workers are willing to accept to enter the industry.

Prediction 4: **Workers inside a cluster will experience faster earnings growth and face steeper earnings-tenure profiles relative to workers outside a cluster.**

The likelihood of receiving a pay increase at an unclustered establishment with any $p \in [p_{min}, p_{max}]$ is zero; firms that do not cluster will have relatively flat wage-tenure profiles, paying workers no more than what is required to hire them from outside the industry and bearing the productivity cost of locating far from other firms. Meanwhile, the probability of receiving a promotion at a clustered establishment is $\gamma[F(p) - F(q(w, p))]$; competition among those establishments that agglomerate acts to drive up earnings levels within firms, with the likelihood of receiving a pay raise in a given firm highest for those with the lowest current wages. Further, workers with longer tenures, who have on average received more offers and who have seen their wages bid relatively high, should not only receive fewer promotions in the future, but also be the least mobile on average since they will tend to be the ones employed by the highest productivity firms.[9]

In sum, competition over labor among heterogeneous firms within a cluster gives rise to greater job mobility as well as inter- and intra-firm wage dispersion. Workers in clusters in the model enjoy upward-

[9] Conditional on the current employer's productivity, mobility will not fall with tenure since $[1 - F(p)]$ is the same for all workers within a given a firm. Hence, while the returns to tenure within a given firm are diminishing in the model, the probability of exiting a given firm at any time is not.

sloping wage-tenure profiles and benefit from past industry experience in securing jobs with good earnings prospects due to the strategic interaction of firms. Individuals at highly productive clustered firms see their wages rise over time as their employers respond to counteroffers from potential poachers, while workers at less productive clustered firms gradually make their way to more productive ones due to poaching.[10] Meanwhile, with no opportunities for on-the-job search and poaching in remote locations, job and earnings mobility are depressed. In contrast to conditions in a cluster, intra-firm wage dispersion is absent and workers face flat earnings-tenure profiles in a region in which a high-technology firm is isolated.

It is worth emphasizing that high productivity firms do not necessarily pay higher or lower wages than low productivity firms in the model. Indeed, a highly productive firm that takes root in an isolated area will pay the same wages as a less productive firm in an isolated area. In a cluster, though, more productive firms will have an edge in attracting and retaining workers, and on average they will pay higher wages and experience fewer separations. Thus, within a cluster, higher productivity firms will tend to be the largest, the highest paying, and the most likely to have workforces with relatively long tenures, all predictions consistent with empirical evidence (Brown and Medoff 1989, Haltiwanger et al. 2000).

4 Data

4.1 Sources

In studying industrial agglomeration and its relationship with local labor market dynamics, I use a new employee-employer matched data set constructed and maintained by the U.S. Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) Program. The LEHD database consists of

[10] Møen (2005) argues that R&D-intensive firms make technical staff "pay" for the knowledge they accrue early in their careers by paying relatively low starting wages, but reward these workers with stronger within-job wage growth and hence higher earnings later in their careers. He contends that these compensation patterns help to explain how the labor market internalizes potential externalities related to the worker mobility.

quarterly records of the employment and earnings of almost all individuals from the unemployment insurance (UI) systems of most U.S. states in the 1990s and early 2000s. An extensive description of these particular data, as well as a comprehensive discussion of the advantages and disadvantages of administrative data more generally, appears in Abowd et al. (2005) and Haltiwanger et al. (2000).[11]

LEHD data boast several advantages over household and business based survey data. The data are current and relatively accurate because there are penalties associated with misreporting. Since the scope of the data is the full universe of employers and workers, we can track movements of workers across earnings categories and across employers. The UI records have also been integrated with internal survey data and administrative records containing information on workers' demographic characteristics, including date of birth, race, sex, and education, which in turn permits us to characterize the workforce composition of individual businesses. Further, LEHD data include a detailed industry classification code (six-digit NAICS) for each establishment that can be used for analyses that exploit cross-industry variation or that focus in on particular sectors. I also integrate data from LEHD's Geographic Address List (GAL), which contains unique commercial and residential addresses for each establishment, including latitude/longitude coordinates.[12]

The LEHD data, while nearly universal in scope and rich in many respects, have several limitations. First, the data are currently available only for a subset of U.S. states, and the amount of historical data varies by state.[13] Second, depending on the state, there is spotty coverage of workers and firms in some

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[11] Because of the sensitivity of these data, they are anonymized before they are used in any Census Bureau projects; all standard identifiers and names are stripped and replaced by unique worker and business identifiers. Only Census Bureau employees or individuals who have Special Sworn Status are permitted to work with the data, and there are serious penalties for disclosing the identity of an individual or business. Any research must be for statistical purposes only, and must be reviewed by the Census Bureau and other data custodians. Under Title 13 of the U.S. code, any breach of confidentiality can result in prosecution in which violators are subject to a $250,000 fine and/or five years in jail.

[12] See Abowd et al. (2005) for details on the GAL.

[13] As of the summer of 2006, 43 states (including the District of Columbia) are participating in the LEHD Program, a voluntary federal-state partnership that integrates data on employees and data on employers with multiple other data sources to produce labor market information about the dynamics of the local economy and society. This is an ongoing project, and additional states are expected to join. For more information on the LEHD Program, see http://lehd.dsd.census.gov.

sectors, including agriculture, non-profits, and public administration.[14] Finally, business identifiers in the LEHD data are State Employer Identification Numbers (SEINs), which are used for state tax collection purposes and are potentially more aggregated business entities than establishments. While this aggregation requires that we impute some measures of workforce composition and earnings for the relatively small number of establishments that are part of larger multi-unit operations,[15] we can nevertheless geographically pinpoint individual establishments within multi-unit SEINs using LEHD data.[16]

4.2 Sample

In this paper, I focus on establishments and workers in the prepackaged software industry (NAICS 5112). The software industry has been the subject of a large body of research on the implications of clustering and is a natural candidate for studying how labor mobility interacts with agglomeration (Saxenian 1994, Fallick et al. 2005). Products in the prepackaged software industry are generally sold in national or international markets, minimizing the importance of product market considerations in driving firms' location decisions (U.S. Government Accountability Office 2006). Further, proximity to natural resources such as bodies of water is relatively unimportant, as is access to upstream suppliers of capital goods. Meanwhile, innovation in the industry over the past decade has been rapid, and anecdotal evidence

[14] See Stevens (2002) for a more detailed description of the LEHD database coverage issues.
[15] Fewer than 10% of establishments in the sample are part of multi-unit firms, though closer to one-fourth of workers in the sample are employed in establishments that are part of multi-unit firms.
[16] While SEINs are potentially more aggregated business entities than establishments, LEHD data provide breakouts of establishments for multi-unit SEINs, which are termed SEIN units. Only for a subset of multi-unit SEINs do we have information on precisely which individuals are employed at each SEIN unit, though we know the geographic location of each SEIN unit and its total employment. Hence, when the unit of work is unknown for a particular worker attached to a multi-unit SEIN, LEHD imputes that workplace based on the worker's place of residence and the distribution of employment across establishments within the SEIN. See Abowd et al. (2005) for details on the imputation procedure.

suggests that labor poaching aimed at appropriating valuable knowledge from rivals occurs and represents a legitimate concern among firms in the industry.[17]

For this study, I use data for one large U.S. state for the third quarter of 1991 through the third quarter of 2003.[18] I chose the sample state based on its size, its representativeness, the relatively long time span of its data, and the quality of the geographic coding of its establishments. Over 2,400 unique software establishments, 153,000 software workers, and 170,000 software jobs (i.e., worker-firm matches) appear in the data over the entire sample period. Additional information regarding the data and descriptive statistics for the sample appear in Appendix 2.

4.3 Measuring Clustering

Researchers have long recognized that in measuring industrial agglomeration, it is critical to control for the general spatial distribution of economic activity. However, most measures of geographic clustering among establishments in different industries still rely on coarse areal data, or data that aggregate points (in this case, establishments) to spatial zones (e.g., counties, metropolitan statistical areas, or states) and cannot be computed at the establishment level (Krugman 1991, Ellison and Glaeser 1997, Duranton and Overman 2005). Not only do aggregated statistics that rely on arbitrary administrative boundaries often provide misleading impressions of the actual extent of clustering a given

[17] Google and Microsoft went to court in the fall of 2005 after a top researcher at Microsoft defected to Google, with Microsoft charging that the move violated a clause in the researcher's contract that precluded him for working for a competitor (Richtel 2005). Such litigation is not without precedent; SAP America sued Siebel in 1999 for allegedly hiring 27 key SAP employees in what SAP deemed "predatory hiring practices… designed to injure SAP's business and damage SAP's ability to compete with Siebel." (Boudette and Davis 1999). In 1997, Borland International sued Microsoft over the defection of 34 key employees to the software maker, claiming that Microsoft was attempting to drive it out of business (Bank 1997). Also in 1997, Informix tried to obtain a restraining order against Oracle after 11 key software engineers left the firm (Richards 1997). The prevalence of non-compete clauses in employee contracts in the software industry also speaks to the importance of retaining critical employees and the private knowledge that they embody. Microsoft, in fact, requires that all employees sign an agreement that prohibits them from divulging trade secrets or working for a competitor for at least one year after leaving the company (Richtel 2005).

[18] I calculate clustering statistics for the sample state alone and hence respect state boundaries, although the measure I construct does not depend on any administrative boundaries within the state and can be applied more generally to a more geographically expansive dataset.

establishment in an area is facing, but they also are ill-suited to the analysis I seek to conduct given my interest in within-industry variation in clustering and its implications for individual worker outcomes.[19]

I adapt the conventional location quotient to examine the extent of clustering at the establishment level.[20] The measure I construct can be applied at a variety of different spatial scales that need not be dictated by administrative boundaries, and it permits a closer evaluation of how clustering relates to other outcomes within a particular industry.[21] The location quotient is a measure of an industry's level of concentration around a particular location and is computed as the ratio of an industry's share of total local establishments or employment relative to its overall share of total establishments or employment. Typically, "local" represents some level of administratively defined sub-national geography, such as state, metropolitan statistical area, or county. Instead, I construct establishment-specific location quotients by drawing circles with radii of five, ten, 25, and 50 miles around each establishment in the sample and computing the industry's share of total establishments or total employment within those rings relative to its share of total establishments or total employment in the state. For establishment j in industry k, the location quotient for a circle with radius r is

$$LQ_{jk}^{r} = (E_{jk}^{r} \ / \ E_{j}^{r}) \ / \ (E_{k} \ / \ E)$$

where E_{jk}^{r} is the number of establishments or employment within the circle of radius r around establishment j in industry k (excluding establishment j), E_{j}^{r} is the number of establishments or employment in all industries within the circle of radius r around establishment j, E_{k} is the number of

[19] Different methods have been developed to overcome at least some of the limitations associated with areal measures of agglomeration (Duranton and Overman 2005, Freedman 2006). The methods advanced in these papers, however, are often either not applicable at the establishment level, and therefore not viable alternatives for evaluations of within-industry clustering patterns, or are extremely computationally burdensome, and therefore impracticable for the type of large-scale empirical analysis I perform.

[20] Holmes and Stevens (2002) develop a similar establishment-specific measure of industrial clustering to explore the relationship between firm size and agglomeration.

[21] For a subsample of establishments, I computed both the distance-based, establishment-level measure of clustering developed in Freedman (2006) as well as the modified establishment-specific location quotient described in this paper and found a correlation coefficient of over 0.90.

establishments or employment in the entire state in industry k, and E is the number of establishments or employment in the state across all industries.

This methodology provides for each establishment a single measure of agglomeration that reflects the extent to which that establishment is more or less clustered with like establishments than is typical for all businesses. Values of the location quotient exceeding one reflect higher than average concentration at a particular location; values less than one indicate less than average concentration.

5 Descriptive Statistics

In this section, I present basic descriptive statistics on the nature and extent of agglomeration in the prepackaged software industry in one state. Unless otherwise noted, I use employment-based clustering measures for the tables and figures. Figure 1 presents the average number of establishments and average employment within five, ten, 25, and 50-mile radii of sample establishments, calculated from 1991 through 2003.

[Figure 1: Average Number of Establishments and Employment for Selected Radii]

Throughout much of the 1990s, the number of establishments as well as employment in NAICS 5112 climbed, reaching a plateau later in the sample period and retreating somewhat after the 2000 recession. Changes over time in the average number of software establishments or employment near sample establishments tell us little, however, about whether establishments in the industry grew more or less clustered relative to the broader spatial distribution of economic activity. The location quotient, computed as the ratio of an industry's share of total local establishments or employment relative to its share of total establishments or employment in the state, sheds light on the degree of clustering over and above what we would expect given the general distribution of economic activity. Table 2 presents clustering statistics for software establishments in the sample over different distances for selected years.

[Table 1: Establishment-Specific Location Quotients for Selected Years]

Establishment-specific location quotients, whether measured using establishments or employment, are well above one in the software industry for circles of up to at least 50 miles, indicating that economic activity in the software industry is quite clustered relative to the broader spatial distribution of economic activity.[22] While average location quotients have held steady if not declined modestly over time on an establishment basis, employment-weighted location quotients rose between the early 1990s and early 2000s. This suggests that while establishments may have begun to locate further apart in recent years, employment in the software industry has grown increasingly concentrated in a few locations.

Although there is a clear tendency toward clustering in the industry, it is not the case that all activity is concentrated in a few locales. Indeed, in 1998 and using a 25-mile radius, only 63% of sample establishments had an establishment-based location quotient greater than one; for the employment-based measure, this figure was 52%. This heterogeneity in the extent of clustering among establishments in any given time period as well as within establishments over time (as other establishments enter and exit in the vicinity of an existing establishment) constitutes the source of variation that permits us to identify relationships between clustering and particular labor market outcomes below.

Workers and firms in a cluster differ from those outside clusters along several immediately observable dimensions. Starting earnings are relatively high among workers in areas where software establishments are agglomerated and, importantly, earnings-tenure profiles for workers in clustered establishments tend to be relatively steep. Figure 2 depicts a plot of annualized earnings for workers in the sample based on a linear regression of earnings on a cubic in tenure.

[Figure 2: Earnings-Tenure Profiles in Clustered and Unclustered Establishments]

[22] By comparison, establishment-based location quotients for department stores (NAICS 4521) in the sample state in the second quarter of 2003 averaged 1.34 (standard deviation 1.03), 1.19 (0.65), 1.08 (0.42), and 1.04 (0.32) at five, ten, 25, and 50 miles, respectively. Employment-based location quotients for the same industry and time period averaged 1.32 (1.30), 1.17 (0.76), 1.06 (0.46), and 1.05 (0.36) at five, ten, 25, and 50 miles, respectively. For further discussion of cross-industry patterns in clustering, see Freedman (2006).

The relationship between earnings-tenure profiles and clustering is striking, but it could reflect differences inside and outside clusters in underlying worker and firm characteristics that are independent of agglomeration. Indeed, as shown in Figure 3, while clustered establishments do not differ substantially from their unclustered counterparts in average educational attainment, gender composition, or average workforce age, clustered establishments tend to be larger, to pay more, and to have more racially diverse workforces.

[Figure 3: Workforce Characteristics of Clustered and Unclustered Establishments]

Hence, central to the empirical analysis that follows will be controlling for worker and firm heterogeneity across locations in an effort to isolate the effects of clustering on labor market dynamics.

6 Empirical Analysis

In this section, we turn to an empirical analysis of how establishment clustering bears on job mobility and earnings patterns in the prepackaged software industry. Testing each of the main predictions of the model identified in Section 3, we examine first industrial clustering's effects on job duration and then its implications for job-hopping within versus between industries. Next, we evaluate whether workers who accept jobs in agglomerated software establishments accept lower wages, and finally we assess whether in clusters any implicit investments that workers make early in their careers in the form of depressed earnings are rewarded later with faster wage growth and steeper earnings-tenure profiles.

6.1 Job Mobility

Clustering in the model facilitates greater job mobility among workers, driving up the probability of separating from a given high-technology establishment and rendering it more likely that, upon separation,

individuals will hop directly from one firm in the industry to another in the same industry. I calculate job separations by comparing worker and establishment matches in consecutive quarters in the data. A separation at time t occurs when a worker is employed at an establishment at t but not at $t+1$; the quarterly separation rate in the data averages 7%.

For job spells that are not right censored, we can distinguish whether workers in NAICS 5112 move to new establishments in the same industry, establishments in different industries, or out of the sample.[23] The majority of separated workers in our sample ultimately transition into new jobs, though most take positions at establishments outside the software industry. Of the 130,127 separations from NAICS 5112 establishments that we observe, about two-thirds (86,786) result in a transition from a software job to a job outside the software industry, while only about 8% (9,873) result in a transition from one software job to another software job. The remainder of the separations from NAICS 5112 establishments result in exit from the sample, which could result due to a right-censored spell of unemployment, withdrawal from the labor force, or because workers obtain a job outside the state. [24]

Prediction 1: **Due to on-the-job search and labor poaching, job durations will be shorter inside a cluster than outside a cluster.**

To test the first prediction of the model empirically, I examine whether clustering among software establishments affects a worker's propensity to separate from his or her current job, controlling for a host of worker and establishment characteristics. I use a panel that includes all new hires in the sample between 1991 and 2003; restricting the sample to new hires eliminates left censoring problems that arise because the data begin with some job spells in progress. The data in this case are organized at the job-quarter level, where a job is defined as unique individual-establishment match. I estimate discrete-time

[23] Those workers in NAICS 5112 whom we observe transition into a new job may experience an intervening spell of non-employment; I do not distinguish between those whom we observe transition directly from one job into another with no intervening spell of non-employment and those whom we observe transition from one job into another with an intervening spell of non-employment.

[24] The data do not permit us to distinguish between involuntary separations and voluntary separations (i.e., between layoffs and quits).

hazard models of the probability that a worker i is observed to separate from establishment j in period t, conditional on not having separated until that time. The discrete-time hazard rate, h_{ijt}, is given by

$$h_{ijt} = Pr(T_{ij} = t \mid T_{ij} \geq t;\ C_{ij},\ \boldsymbol{X}_{it},\ \boldsymbol{Z}_{jt})$$

where T_{ij} is a discrete random variable representing the quarter in which job spell ij ends, $\boldsymbol{X}_{it}$ is a vector of characteristics for worker i at time t, and $\boldsymbol{Z}_{jt}$ is a vector of characteristics for establishment j at time t.[25] Worker and firm characteristics may or may not vary over time. C_{ij} represents a job-specific, time-invariant indicator for clustering equal to one if establishment j has an employment-weighted location quotient (measured using a 25-mile radius) greater than or equal to one in the majority of the quarters over which the spell ij is observed.[26] A logistic re-parameterization of the hazard is

$$h_{ijt} = 1/[1 + exp(-\zeta(t) - \beta C_{ij} - \boldsymbol{\Phi X}_{it} - \boldsymbol{\Omega Z}_{jt})]$$

such that

$$log[h_{ijt}/(1- h_{ijt})] = \zeta(t) + \beta C_{ij} + \boldsymbol{\Phi X}_{it} + \boldsymbol{\Omega Z}_{jt}$$

where, in my preferred fully semi-parametric specification, the baseline hazard $\zeta(t)$ consists of dummy variables for each period.[27] In contrast to continuous-time versions of survival models that assume a non-

[25] I include in $\boldsymbol{Z}_{jt}$ county dummies, which help to capture urbanization effects as well as any differences across counties in tax structures and incentives, infrastructure, public services, etc. Using instead an MSA/non-MSA dummy or a variable for total employment across all industries within 25 miles has little effect on coefficient estimates for the variables of interest.

[26] The results are robust to using an establishment-based location quotient and to using radii less than 25 miles in the calculations.

[27] As robustness checks, I also estimate log-time and cubic polynomial model specifications. The results from these alternative specifications are very similar both qualitatively and quantitatively to the results from the fully semi-parametric specification. Also, while for expositional purposes I use a time-invariant indicator for clustering in the

constant hazard (for example, the Weibull), the discrete-time model can capture non-monotonous changes in the baseline hazard. I assume there exists no unobserved heterogeneity and estimate using maximum likelihood. A single individual in the sample can potentially separate more than once from different software jobs, and since the observations for each person are likely not independent over time, I also correct standard errors by clustering on person.

[Table 2: Discrete-Time Proportional Hazard Models]

The results in Table 2 indicate that, controlling for other worker and firm characteristics, clustering in the software industry is associated with abbreviated job spells. The implied odds ratio suggests that being employed at a clustered software establishment increases the likelihood of separating by a statistically and economically significant 8% relative to being employed at an establishment that is not clustered.

Interestingly, prior industry experience boosts the likelihood of separating by over 20%. The effect of prior experience on the probability of separation is larger among establishments in clusters than outside clusters. Not surprisingly, higher earnings reduce the probability of separation substantially, which is consistent with the model I present in this paper as well as more generally with the theoretical literature on job search and matching. That the negative relationship between earnings and the probability of separation is stronger among clustered establishments, though, is not a prediction of other models but, to the extent that those with higher earnings tend to be employed at the most productive firms in a cluster, does follow from the model in this paper. Also consistent with the model is that separations are less likely at large firms within a cluster; larger firms in the model are those that are more productive and that would tend to amass the greatest number of highly tenured employees. This pattern does not hold among firms outside clusters, in line with the predictions of the model and distinct from competing hypotheses.

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discrete-time hazard models I present, the results are robust to instead using a quadratic in the time-varying location quotient.

Overall, while the results of the hazard models suggest that clustering tends to be associated with a more rapid rate of worker turnover in the software industry, they reveal little about the outcomes of worker-firm separations. We now turn to a deeper analysis of these outcomes.

Prediction 2: **Job-hopping within an industry will be more prevalent inside a cluster than outside a cluster.**

I next investigate how clustering among software establishments affects where separated workers wind up. I estimate a multinomial logit model aimed at revealing whether employment in a cluster bears on one's likelihood of taking a job with another establishment in the same industry as opposed to an establishment in another industry or dropping out of the sample, conditional on having separated from a job in the software industry and controlling for a worker's characteristics and the characteristics of the establishment from which he or she separates.

Let $S = \{Transition\ to\ Same\ Industry,\ Transition\ to\ Different\ Industry,\ Transition\ Out\ of\ Sample\}$ denote the set of outcomes facing each individual i employed at an establishment j in time t but not $t+1$. I condition the individual's present work status $s_{it} = s$ to be in the software industry and estimate a model to evaluate the probability of landing in each destination state $k \in S$ at time $t+\tau$ upon separating ($\tau \geq 1$). In implementing the multinomial logit model, I set the reference transition category as transitioning into a new job that is not in the software industry. I estimate the following:

$$Pr(s_{it+1} = k \mid s_{it} = s;\ C, \boldsymbol{X}, \boldsymbol{Z}) = 1/\,[1 + \textstyle\sum_{k \in S} exp(\beta^k C_{ij} + \boldsymbol{\Phi}^k \boldsymbol{X}_{it} + \boldsymbol{\Omega}^k \boldsymbol{Z}_{jt})]\ ,$$

$$k = Transition\ to\ Different\ Industry$$

$$Pr(s_{it+1} = k \mid s_{it} = s;\ C, \boldsymbol{X}, \boldsymbol{Z}) = exp(\beta^k C_{ij} + \boldsymbol{\Phi}^k \boldsymbol{X}_{it} + \boldsymbol{\Omega}^k \boldsymbol{Z}_{jt})/[1 + \textstyle\sum_{k \in S} exp(\beta^k C_{ij} + \boldsymbol{\Phi}^k \boldsymbol{X}_{it} + \boldsymbol{\Omega}^k \boldsymbol{Z}_{jt})],$$

$$k = Transition\ to\ Same\ Industry,\ Transition\ Out\ of\ Sample$$

where C_{ij} represents a dummy for firm clustering over the duration of the software job spell defined by the worker-firm match ij, $\boldsymbol{X}_{it}$ is a vector of individual-level covariates for worker i at the time of

separation t, and $\boldsymbol{Z}_{jt}$ is a vector of establishment-level covariates at the time of separation t.[28] β^k and the vectors $\boldsymbol{\Phi}^k$ and $\boldsymbol{\Omega}^k$ are coefficients affecting the likelihood of transitioning to future work status $k \in S$. A dummy for left censoring is interacted with all terms subject to such censoring, and I cluster the errors on person.[29]

[Table 3: Multinomial Logit Model]

Not only are workers in software clusters more likely to separate, but as the results in Table 4 reveal, they are also are more likely to transition to other firms in the same industry when they leave a software establishment. Taking exponents of the coefficients, workers in a cluster are over one-third more likely to transition within the same industry rather than to a firm in a different industry all else equal, a result consistent with the model presented above.[30] The likelihood of transitioning to an establishment in software rather than another industry is increasing in earnings at the separation establishment, tenure at the separation establishment, the size of separation establishment, and whether an individual had software industry experience prior to working at the separation establishment. Though the model implies that, relative to the probability of transitioning to a firm in a different industry, the probability of moving from one firm in the high-technology industry to another firm in the same industry should be decreasing in current earnings, tenure, firm size, and prior industry experience (at least on a cross-sectional basis) given

[28] I include in $\boldsymbol{Z}_{jt}$ county dummies; using instead an MSA/non-MSA dummy or a variable for total employment across all industries within 25 miles has little effect on coefficient estimates for the variables of interest.

[29] One assumption of the multinomial logit model is that outcome categories for the model have the independence of irrelevant alternatives (IIA) property. That is, the inclusion or exclusion of categories should not affect the relative risks associated with the regressors in the remaining categories. Hausman tests for IIA conducted by excluding each outcome category in turn indicate in each case that we cannot reject the null hypothesis that the odds of one outcome occurring are independent of other alternatives. Under IIA, we would expect no systematic change in the coefficients if we excluded one of the outcomes from the model; Hausman tests yield Chi-squareds sufficiently small that we cannot reject the nulls that differences in the coefficients between the models are not systematic. Results from Small-Hsiao tests for IIA generally corroborate this conclusion, though not always consistently (the Small-Hsiao test is based on splitting the sample and results therefore vary somewhat by execution).

[30] A Wald test for the significance of the clustering variable across all outcome categories (in which the null hypothesis is that all coefficients associated with the variable are zero) indicates that it is significant at the 0.01 level in all specifications, regardless of the radius chosen for the location quotient, and regardless of whether the location quotient is establishment-based versus employment-based. Using a quadratic in the location quotient instead of a dummy yields similar results.

that each should be positively correlated with establishment productivity, we might expect all these to serve as signals to potential poachers that the worker has accumulated valuable knowledge that he or she could bring to a new job.[31]

With respect to other covariates, greater formal education and lower age, while not significantly affecting the relative likelihood of staying within software or switching industries, tend to boost the odds of dropping out of the sample, perhaps because younger and better educated workers are more willing to move out of state when better job opportunities arise. Meanwhile, upon separating from software industry jobs, males are less likely than females to drop out of the sample and modestly more likely than females to take new positions at other software firms as opposed to jobs in other industries.

6.2 Earnings Dynamics

This section is devoted to empirical exercises designed to shed light first on whether workers who obtain jobs in clustered establishments accept lower wages, and second on whether workers are rewarded for these implicit investments with stronger wage growth and higher earnings later in the careers.

Prediction 3: **Inside a cluster, workers transitioning into the industry will accept a drop in earnings, whereas workers outside a cluster will not.**

With respect to earnings changes for individuals transitioning into jobs at clustered versus unclustered software establishments from jobs outside the sector, the model suggests that individuals will accept lower initial earnings at clustered establishments with the expectation that, due to the heightened competition over labor in clusters, their earnings will be bid up over time once they get their foot in the door in the industry. Workers starting in a different industry who take a job at an isolated software

[31] Wald tests for combining outcome categories yield strong rejections of the null hypotheses that all coefficients (except intercepts) associated with a given pair of outcomes are zero, or, in other words, that categories can be collapsed. That is, for all combinations of categories, we can reject the hypothesis that our variables do not differentiate between categories. Hence, we cannot combine any outcome types. This holds in all specifications regardless of the radius chosen for the location quotient and regardless of whether the location quotient is establishment-based versus employment-based.

establishment, meanwhile, should not be willing to accept a discount given that their outside opportunities are at least as attractive in terms of expected long-term earnings. To test this prediction, I estimate a treatment-effects model on a sample of individuals whom we observe transition from a job outside the software industry into a job within the software industry. The primary regression equation of interest is

$$ln(earnings)_{ilt} - ln(earnings)_{ijt-\tau} = \alpha + \beta_1 C_{il} + \boldsymbol{\Phi}(\boldsymbol{X}_{it} - \boldsymbol{X}_{it-\tau}) + \boldsymbol{\Omega}(\boldsymbol{Z}_{lt} - \boldsymbol{Z}_{jt-\tau}) + \eta_t + \eta_{t-\tau} + \varepsilon_{i(j,l)t} ,$$

$$j \text{ outside NAICS 5112, } l \text{ in NAICS 5112}$$

The dependent variable is the change in log annualized real earnings for worker i between a new job in software at establishment l (obtained at time t) and a prior job not in software at establishment j (left at time $t-\tau$, $\tau \geq 1$).[32] On the right-hand side of the regression, C_{il} is a dummy variable that takes on a value of one if the transition into software from outside the industry is into a job at a firm that is clustered over the duration of the spell defined by the worker-firm match il, $\boldsymbol{X}_{it}$ ($\boldsymbol{X}_{it-\tau}$) is a vector of individual i's characteristics at t ($t-\tau$), $\boldsymbol{Z}_{lt}$ ($\boldsymbol{Z}_{jt-\tau}$) is a vector of establishment l's characteristics at t (j's characteristics at $t-\tau$), η_t and $\eta_{t-\tau}$ are time dummies, and $\varepsilon_{i(j,l)t}$ is an error term that we assume is independent across individuals but not necessarily within individuals over time.

The possibility that workers self-select at the beginning of their software careers into jobs at clustered or unclustered software establishments raises a potential endogeneity problem. I address this issue by assuming that the binary variable C_{il} in the primary regression arises from an unobservable latent variable C_{il}*, where

$$C_{il}^* = a + b_1 C_{il} + \boldsymbol{c}_1 \boldsymbol{X}_{it} + \boldsymbol{c}_2 \boldsymbol{X}_{it-\tau} + \boldsymbol{d}_1 \boldsymbol{Z}_{lt} + \boldsymbol{d}_2 \boldsymbol{Z}_{jt-\tau} + \eta_t + \eta_{t-\tau} + u_{i(j,l)t}$$

[32] More specifically, the right-hand side variable is log annualized real ($1997) earnings in the first full quarter of the new job minus log annualized real earnings in the last full quarter of the previous job. Workers transitioning from a job outside NAICS 5112 into a job in the industry may experience an intervening spell of unemployment, but a previous spell in a different industry must be observed (the software job spell in question cannot be left censored).

The decision to obtain the treatment (in this case, the decision to take a job at a clustered establishment) is made according to the rule $C_{il} = 1$ if $C_{il}^* > 0$ and $C_{il} = 0$ otherwise. This estimation approach, which I carry out using maximum likelihood, mitigates bias caused by correlation of the regressor with omitted variables in the primary regression by adding a term to the regression that represents the non-zero expectation of the error term.[33] Hence, we can obtain a more reliable estimate of the effect of obtaining a job at a clustered as opposed to an unclustered establishment on the change in earnings workers experience as they move into the software industry from outside the industry.

[Table 4: Earnings Consequences of Job Transitions into Software]

As the results in Table 4 show, controlling for other characteristics, workers coming from outside the industry who take jobs at software firms, while on average enjoying initial earnings gains, tend to experience a roughly 2% smaller change in log annualized earnings when they obtain jobs at clustered as opposed to unclustered establishments.[34] For a worker whose real annualized earnings at the end of his or her prior non-software job was $52,000, the average for the sample, this translates into an over $1000 differential. In other words, correcting for possible self-selection into clustered or unclustered establishments at the start of their software careers, workers who obtain jobs at clustered establishments receive smaller increases in earnings than those who obtain jobs at unclustered establishments. Though the model does not predict an initial earnings increase for workers transitioning from outside the industry into either clustered or unclustered high-technology firms, the results are consistent at least in spirit with the proposition that those who obtain jobs in clustered establishments may be willing to accept lower

[33] The error terms $\varepsilon_{i(j,l)t}$ and $u_{i(j,l)t}$ are assumed to have a bivariate normal distribution with zero mean. The estimated correlation between error terms is positive (but not highly significant), suggesting that the estimated effect of treatment from single-equation estimation will be biased away from zero (albeit only slightly so).

[34] The results from the model are robust to a variety of specifications for the treatment regression as well as to the use of the two-step estimator as opposed to the maximum likelihood estimator. See Greene (2003) for a discussion of treatment-effects models.

wages early in their careers in the high-technology industry in exchange for brighter long-term earnings prospects.

Turning to other covariates in the primary regression, transitioning into a software firm that is large relative to the establishment at which an individual previously worked has positive earnings consequences, as does changing one's county of employment due to taking a job in the industry. On the other hand, the more time that has elapsed between jobs (measured by the change in age between spells) tends to depress (albeit insignificantly) the change in earnings that results from the transition. This latter fact may reflect skill obsolescence and/or any negative signal a longer spell of unemployment might send to future employers.

Prediction 4: **Workers inside a cluster will experience faster earnings growth and face steeper earnings-tenure profiles relative to workers outside a cluster.**

In the model, individuals enjoy relatively steep wage-tenure profiles in high-technology industry clusters as firms compete over skilled labor. To examine how clustering in the software industry affects workers' earnings-tenure profiles, I estimate a series of panel regressions taking full advantage of the longitudinal aspects of the matched employee-employer data. In these regressions, I use various techniques to control for both observable and unobservable worker and firm characteristics in order to isolate the true effect of clustering on earnings patterns.

I begin by modeling heterogeneity across workers and establishments explicitly by assuming that each job has its own specific intercept, $\alpha + \theta_{ij}$. This fixed effect (FE) model, which eliminates both unobserved worker-level and establishment-level time-invariant error components, is specified as follows:

$$ln(earnings)_{ijt} = \alpha + \beta_1 LQ_{jt} + \beta_2 LQ_{jt}^2 + \beta_3 tenure_{ijt} + \beta_4 tenure_{ijt}^2 + \beta_5(LQ_{jt}*tenure_{ijt}) +$$

$$\beta_6(LQ_{jt}*tenure_{ijt}^2) + \beta_7(LQ_{jt}^2*tenure_{ijt}) + \beta_8(LQ_{jt}^2*tenure_{ijt}^2) + \boldsymbol{\Phi X}^*_{it} + \boldsymbol{\Omega Z}^*_{jt} + \theta_{ij} + \eta_t + \varepsilon_{ijt}$$

where $ln(earnings)_{ijt}$ is the natural log of full-quarter earnings of worker i at establishment j at time t, LQ_{jt} is the establishment-specific time-varying location quotient for establishment j at t, $tenure_{ijt}$ is accumulated tenure for i at j as of t, $\boldsymbol{X}_{it}$ represents a vector of person characteristics at t, $\boldsymbol{Z}_{jt}$ represents a vector of establishment characteristics at t, and η_t is a time dummy.[35] Since the observations for each job are likely not independent over time, I correct standard errors by clustering on each establishment-worker pair; that is, the error term ε_{ijt} is assumed independent across jobs but not necessarily within jobs over time. With the inclusion of the squared location quotient term, I allow for some degree of non-linearity in the relationship between clustering and earnings. I interact the location quotient with tenure to shed light on how clustering affects the shape of the earnings-tenure profile. Though not explicit in the specification, a dummy for left censoring is interacted with all terms subject to such censoring.

An attractive feature of the FE approach is that it helps to mitigate any ability bias that might arise because more inherently talented workers self-select into clustered establishments. This would tend to bias estimates of the earnings effects of clustering upward. Using job fixed effects, which are again defined for each unique worker-establishment match, also mitigates potential problems stemming from firms' endogenous location decisions; as the model suggests, whether a firm decides to cluster or not depends on its assessment of the benefits and costs associated with labor pooling and poaching, which in turn hinge on the firm's own level of productivity. While each firm's productivity is unobservable to us, to the extent that some perception of it on the firm's part informs its location decision and to the extent that productivity is time invariant, job fixed effects will resolve the endogeneity problem associated with firm location choice. Meanwhile, including time dummies eliminates any bias due to a correlation between clustering and earnings resulting from shocks that vary over time but are constant across jobs.

The FE approach permits the error terms to be correlated with the job effects, but the inclusion of fixed job effects drastically diminishes the number of degrees of freedom in the regression and precludes us from obtaining parameter estimates for time-invariant worker and establishment characteristics. In the

[35] I include in $\boldsymbol{Z}_{jt}$ county dummies; using instead an MSA/non-MSA dummy or a variable for total employment across all industries within 25 miles has little effect on coefficient estimates for the variables of interest.

FE framework, these time-invariant characteristics are subsumed by the unit-specific intercepts, which are assumed to be non-stochastic. Further, FE models are vulnerable to measurement error because such models are, in essence, difference-based as opposed to level-based. This vulnerability could bias results from a FE model toward zero.

As they are level-based rather than difference-based, random effects (RE) models are less sensitive to measurement error. Furthermore, RE models permit us to obtain coefficient estimates for time-invariant worker and establishment characteristics and are not subject to the same degrees-of-freedom problems to which FE models are prone. Therefore, as a check and extension on my preferred FE approach, I estimate an RE model that assumes that the earnings intercept for a particular job is a random variable that is uncorrelated with observable person and firm characteristics. The RE specification is

$$ln(earnings)_{ijt} = \alpha + \beta_1 LQ_{jt} + \beta_2 LQ_{jt}^2 + \beta_3 tenure_{ijt} + \beta_4 tenure_{ijt}^2 + \beta_5(LQ_{jt}*tenure_{ijt}) +$$

$$\beta_6(LQ_{jt}*tenure_{ijt}^2) + \beta_7(LQ_{jt}^2*tenure_{ijt}) + \beta_8(LQ_{jt}^2*tenure_{ijt}^2) + \boldsymbol{\Phi X}_{it} + \boldsymbol{\Omega Z}_{jt} + \eta_t + \{e_{ij} + \varepsilon_{ijt}\}$$

where e_{ij} is a job-specific error term, assumed to be orthogonal to job characteristics, i.i.d. across jobs with mean zero and variance σ_v^2 (with $0<\sigma_v^2<\infty$), and independent of ε_{ijt}. All other variables are defined as before, and again, left-censoring dummies are incorporated in the RE model where required.

While the RE approach holds some advantages over the FE approach, it is sensitive to assumptions on the statistical properties of the random variables, and in particular the independence of e_{ij} and job or person characteristics. Failure of this assumption would mean that the RE model would yield inconsistent parameter estimates; the potential for violating this assumption and the resulting inconsistency motivates my preference for the FE approach.

[Table 5: Worker-Level Panel Earnings Regressions]

The results of the FE and RE regressions appear, along with pooled OLS results for comparison,[36] in Table 5.[37] Earnings are increasing both in the extent to which software firms are clustered and in worker tenure, regardless of specification.[38] Furthermore, as the interaction terms reveal, workers employed at clustered establishments reap relatively large returns to tenure controlling for other worker and firm characteristics. In line with the model's predictions, therefore, workers in clusters face steeper earnings-tenure profiles, which the theory outlined in this paper explains is the result of the strategic interaction of high-technology firms as they compete over skilled labor in agglomerated areas. The results also reveal that larger establishments pay more on average than smaller establishments, which is consistent with the model as well as with findings in past literature (Davis and Haltiwanger 1996).

Importantly, in the FE specification, job fixed effects absorb the impacts of unobservable characteristics that one might otherwise expect to cloud estimates of clustering's effect on earnings patterns. As I discussed previously, the fixed effects furthermore help to resolve selection and endogeneity problems that could arise in cross-sectional analyses of the relationship of agglomeration and earnings patterns. Nonetheless, the RE model generates coefficient estimates of similar magnitude and significance as the FE model for the main variables, and also sheds light on how various time-invariant worker characteristics influence earnings.[39] Earnings are higher for workers who are male, white, more educated, and who possess past industry experience.

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[36] The pooled OLS model includes time dummies but ignores heterogeneity across jobs beyond basic observable characteristics of workers and the firms at which they are employed. I estimate the equation

$$ln(earnings)_{ijt} = \alpha + \beta_1 LQ_{jt} + \beta_2 LQ_{jt}^2 + \beta_3 tenure_{ijt} + \beta_4 tenure_{ijt}^2 + \beta_5(LQ_{jt}*tenure_{ijt}) + \beta_6(LQ_{jt}*tenure_{ijt}^2) + \beta_7(LQ_{jt}^2*tenure_{ijt}) + \beta_8(LQ_{jt}^2*tenure_{ijt}^2) + \boldsymbol{\Phi X}_{it} + \boldsymbol{\Omega Z}_{jt} + \eta_t + \varepsilon_{ijt}$$

where the variables are defined as they are in the FE and RE models in the text. The results from the pooled OLS model are qualitatively similar to those from the FE and RE models, though clustering and its interaction with tenure have slightly stronger positive effects on earnings in the OLS results.

[37] An F test for the null hypothesis that $\theta_{ij} = 0$ for $ij = 1, 2, \ldots$ in the FE model leads to rejection at the 1% level (F(170,195, 1,352,582) = 25.40). A Breusch and Pagan Lagrange multiplier test for the RE model yields a Chi-squared statistic of 6.0e+06, leading us to the rejection at the 1% level of the null hypothesis that $e_{ij} = 0$.

[38] Qualitatively similar, albeit not as significant, results hold when one uses the establishment-based location quotient. The choice of location quotient radius also has little effect on the results.

[39] Hausman tests of corresponding fixed effect and random effect models generates Chi-squared statistic of 672.64, implying that we can reject the null hypothesis that the coefficients in the two models do not statistically differ. This suggests that, given that the model is correctly specified, the coefficients from the RE model may not be consistent.

In sum, the higher level of pay and steeper earnings-tenure profiles among workers in clusters are consistent with the idea that industrial agglomeration not only may benefit high-technology firms by allowing them to tap into pools of skilled labor, but also fosters competition over workers that bears on their compensation strategies.[40]

7 Conclusion

This paper takes advantage of new employee-employer matched micro-data from the U.S. Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) Program to examine the implications of industrial clustering for labor mobility and earnings dynamics. I find evidence consistent with the predictions of a model in which clustering not only makes it easier for firms to hire workers with industry-specific skills (labor market pooling), but also makes it more likely that firms will lose workers or be forced to pay higher wages because of competition from nearby rivals (labor market poaching). Specifically, I find that workers in clustered establishments in the prepackaged software industry tend to have shorter job durations, are more likely to job hop to other software establishments, and experience steeper earnings-tenure profiles than workers in more remote software establishments, controlling for worker and establishment heterogeneity.

This work opens up numerous avenues for future research. While contributing to the theoretical literature on industrial clustering, I concentrate on the predictions of a model of agglomeration that relate to clustering's consequences for worker job mobility and earnings dynamics; the model also has implications for the location decisions of firms. While I have not yet fully developed its elements on this dimension, the model provides fertile ground for further theoretical exploration of how firm and industry

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Hence, placing more emphasis on the fixed-effect results may be warranted, though most of the coefficients of interest vary little between the two models.

[40] Why workers do not move to arbitrage away differences in lifetime earnings is an open question, though an individual's choice of location could be constrained by family considerations or dependence on multiple sources of income in the household. Additionally, workers could get disutility from the increased employment and earnings volatility that accompanies living in a cluster.

characteristics could influence the spatial distribution of economic activity. Even just heuristically, the model generates a number of additional testable predictions regarding firms' location choices; with information on productivity and profitability available for at least a subset of the establishments in the sample, a clear next step in my research is to bring these predictions to the data.

With respect to the empirical analysis in this paper, a more careful treatment of endogeneity issues in the job mobility and earnings regression may be warranted; though the geographic mobility of workers is limited in reality, it is nonetheless the case that some individuals may self-select into existing clusters of firms. To the extent that those who do so are more prone to job hopping and more likely to receive pay raises, this simultaneity problem would bias upward estimates of clustering's effects on job mobility and earnings growth. Also, conducting a more thorough cross-industry analysis could shed further light on the robustness of the results as well as on the precise nature of the benefits and costs that firms face when clustering. In sectors in which industry-specific skills are less important, such as in retail trade, any gains to clustering stemming from the labor market would likely quickly be overwhelmed by the costs associated with the heightened competition over workers, providing an incentive for businesses to disperse that, in concert with other drivers of employer location decisions, would affect the geographic distribution of firms and thereby shape patterns of local labor market dynamics.

Appendix 1

In this appendix, I provide mathematical details and describe equilibrium conditions of the model outlined in the text.

A.1 Labor Market Conditions Inside an Industry Cluster

Let V_0 be the lifetime utility of a worker in industry L and let $V(w, p)$ be the utility of a worker when employed in industry H at a firm with productivity p at a wage w. Given random matching, workers in the L industry receive wage offers from the sampling distribution $F(x)$ at a rate λ. Hence, with linear utility and discounting, the value associated with working in the L industry solves the following Bellman equation:

$$(\rho + \lambda)V_0 = b + \lambda[1 - F(b)]E_p[V(w'_0(p), p) \mid p > b] + \lambda[F(b)]V_0$$

Given that the lower support of the distribution of marginal productivities among H-types is b,

$$(\rho + \lambda)V_0 = b + \lambda E_p[V(w'_0(p), p)]$$

Any H-type that meets a worker in industry L will make the lowest possible wage offer to hire the worker, which in this case equals the opportunity cost of employment in industry L, V_0. That is, with firms fully informed about workers' reservation wages, we have for all $x \in [p_{min}, p_{max}]$ that $V(w'_0(x), x) = V_0$. Substituting this into the above expression, we have

$$\rho V_0 = b$$

Workers in a cluster who are already employed in the H industry also receive wage offers from the sampling distribution $F(x)$, but at a rate γ.

[Figure A.1: Possible Outcomes of Bertrand Competition]

Figure A.1 depicts the three different possible outcomes of Bertrand competition over a worker between two H-type firms in a cluster under the simplifying assumption that F is uniform: a worker could end up switching jobs (when $p^r > p$), receiving a wage increase at his or her current employer (when $q(w, p) < p^r \leq p$), or experiencing no change in his or her employment status or wage (when $p^r \leq q(w, p)$).[41]

The maximum wage a worker can earn at a firm with productivity p is exactly p, and therefore the maximum utility a worker can achieve from being at a firm with productivity p is $V(p, p)$. Hence, a worker will move to a firm of type $p^r > p$ if the higher productivity firm offers at least the wage $w'(p, p^r)$ defined by

$$V(w'(p, p^r), p^r) = V(p, p).$$

Similarly, in the case in which $q(w, p) < p^r \leq p$, the worker will receive a promotion to the wage $w'(p^r, p)$; this wage represents the optimal offer a firm with productivity p could make to a firm with productivity $p^r \leq p$ that the worker would be willing to accept. The Bellman equation for the value function associated with working in the H industry at a firm with productivity p at a wage w, $V(w, p)$, is then

[41] More generally, while $q(w, p)$ will always be increasing in p and will never cross the 45° line, it need not be concave.

$$(\rho + \delta + \gamma[1 - F(q(w, p))])V(w, p) = w + \gamma[1 - F(p)]E_{p^r}[V(w'(p, p^r), p^r)| p^r > p] + \gamma[F(p) - F(q(w, p))]E_{p^r}[V(w'(p^r, p), p)| q(w, p) < p^r \leq p] + \delta V_0$$

On the right-hand side of the expression, we have the flow wage plus the expected value associated with being poached by another more productive firm, which happens with probability $\gamma[1 - F(p)]$ and in which case the worker receives the value of having the new wage offer $w'(p, p^r)$ and being employed at the new p^r firm; plus the expected value associated with being approached by an alternative employer whose productivity is less than or equal to that of his or her current employer but whose offer acts to boost his or her wage as the firms compete and bid it up to $w'(p^r, p)$; plus the value associated with being exogenously separated from the H industry job.

If $p^r > p$, then the poaching firm hires the worker at wage such that $V(w'(p, p^r), p^r) = V(p, p)$; that is, the more productive firm will never pay more than the amount that makes the worker indifferent between being at the two firms and that the less productive firm is willing to pay. Likewise, if $q(w, p) < p^r \leq p$, the worker's new wage $w'(p^r, p)$ must be such that $V(w'(p^r, p), p) = V(p^r, p^r)$. Thus, we can substitute to get

$$(\rho + \delta + \gamma[1 - F(q(w, p))])V(w, p) = w + \gamma [1 - F(p)]V(p, p) + \gamma[F(p) - F(q(w, p))]E_{pr}[V(p^r, p^r)| q(w, p) < p^r \leq p] + \delta V_0$$

To obtain an expression for $V(p, p)$, the value of working at an H-type firm with productivity p at the highest wage it would be willing to pay, we impose $w = p$,

$$(\rho + \delta + \gamma[1 - F(p)])V(p, p) = p + \gamma[1 - F(p)]V(p, p) + 0 + \delta V_0$$

This implies after some cancellation that

$$V(p, p) =(p + \delta V_0)/(\rho + \delta)$$

Substituting this expression back into the original Bellman equation, replacing the expectation operator by an integral, and noting that $q(p, p) = p$, we get the Bellman equation associated with the value of working in the H-industry at a wage w in a firm with productivity p,

$$(\rho + \delta + \gamma[1 - F(q(w, p))])V(w, p) = w + \gamma[1 - F(p)][(p + \delta V_0)/(\rho + \delta)] + \gamma\int_{q(w, p)}^{p}[(x + \delta V_0)/(\rho + \delta)]dF(x) + \delta V_0$$

The lowest productivity firm in the H industry from which an H-type firm with productivity p that offers a wage w can successfully attract a worker is one with productivity $q(w, p)$. Therefore,

$$\begin{aligned} V(w, p) &= V(q(w, p),q(w, p)) \\ &= [q(w, p) + \delta V_0]/(\rho + \delta) \end{aligned}$$

Using this result to substitute into the previously derived Bellman equation,

$$\begin{aligned} (\rho + \delta + \gamma[1 - F(q(w, p))])\{(q(w, p) + \delta V_0)/(\rho + \delta)\} &= w \\ &+ \gamma[1 - F(p)][(p + \delta V_0)/(\rho + \delta)] \\ &+ \gamma\int_{q(w, p)}^{p}[(x + \delta V_0)/(\rho + \delta)]dF(x) \\ &+ \delta V_0 \end{aligned}$$

Integrating by parts yields

$$(\rho + \delta + \gamma[1 - F(q(w, p))])\{(q(w, p) + \delta V_0)/(\rho + \delta)\} = w + \gamma[1 - F(p)][(p + \delta V_0)/(\rho + \delta)] + [\gamma/(\rho + \delta)]\{(p + \delta V_0)F(p) - [q(w, p) + \delta V_0]F[q(w, p)]\}\int_{q(w, p)}^{p} F(x)dx + \delta V_0$$

Distributing and rearranging terms,

$$(\rho + \delta)q(w, p) = (\rho + \delta)w - \gamma[1 - F(q(w, p))]q(w, p) - (\rho + \delta)\delta V_0 - \gamma[1 - F(q(w, p))]\delta V_0 + \gamma[1 - F(p)]p + \gamma[1 - F(p)]\delta V_0 + \gamma F(p)p + \gamma F(p)\delta V_0 - \gamma F(q)q + \gamma F(q)\delta V_0 - \int_{q(w, p)}^{p} F(x)dx + (\rho + \delta)\delta V_0$$

Hence, with some additional cancellation of terms, we arrive at an expression for the threshold productivity level,[42]

$$q(w, p) = w + \gamma/(\rho + \delta) \int_{q(w, p)}^{p} [1 - F(x)]dx$$

Turning to the derivation of the threshold wage offered by a potential poacher with $p^r > p$, we substitute in $w'(p, p^r)$ for w in the expression for $q(w, p)$ and use that $q(w'(p, p^r), p^r) = p$ to get

$$p = w'(p, p^r) + \gamma/(\rho + \delta)\int_{p}^{p^r} [1 - F(x)]dx$$

So for a potential poacher with $p^r > p$,[43]

$$w'(p, p^r) = p - \gamma/(\rho + \delta)\int_{p}^{p^r} [1 - F(x)]dx$$

We can derive a similar equation for the offer made to a worker in the L industry who is earning b. Recalling that for $x \in [p_{min}, p_{max}]$, $V(w'_0(x), x) = V_0$, and since $w'_0(p) = w'(q(w'_0(p)), p) = w'(b, p)$,[44]

$$w'_0(p) = w'(b, p) = b - \gamma/(\rho + \delta)\int_{b}^{p} [1 - F(x)]dx$$

A.2 Labor Market Conditions Outside an Industry Cluster

The value function for an L-industry worker in an unclustered area depends on the flow wage b plus the value associated with being picked up by a firm in the H industry, which happens at a rate λ:

$$(\rho + \lambda)V_0 = b + \lambda E_0[V(w'_0(x), x)]$$

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[42] If F is uniform and given $p_{min} = b$,

$$q(w, p) = w + [\gamma/(\rho + \delta)]\{[p - q(w, p)]/(p_{max}-b)\}\{p_{max}-(1/2)[p + q(w, p)]\}$$

[43] If F is uniform and given $p_{min} = b$,

$$w'(p, p^r) = p - [\gamma/(\rho + \delta)]\{(p^r - p)/(p_{max}-b)\}\{p_{max}-(1/2)(p^r + p)\}$$

and therefore

$$\partial w'(p, p^r)/\partial p = - [\gamma/(\rho + \delta)][(p - p_{max})/ (p_{max}-b)] > 0$$

$$\partial w'(p, p^r)/\partial p^r = - [\gamma/(\rho + \delta)][(p_{max}- p^r)/ (p_{max}-b)] < 0$$

[44] If F is uniform and given $p_{min} = b$,

$$w'_0(p) = b - [\gamma/(\rho + \delta)] \{(p - b)/(p_{max}-b)\}\{p_{max}-(1/2)(p + b)\}$$

We have for all $x \in [p_{min}, p_{max}]$ that $V(w'_0(x), x) = V_0$. Substituting this into the above expression, we have $\rho V_0 = b$. The lack of other H-types with which to compete over workers implies $\gamma = 0$, which in turn gives us the Bellman equation for the value to a worker of being in an unclustered area and working at an H-type firm with productivity p:

$$(\rho + \delta)V(w, p) = w + \delta V_0$$

Thus, $w'_0(x) = w'(b, x) = b$, and we have $V(w, x) = V(b, x) = V_0$ for all $x \in [p_{min}, p_{max}]$.

A.3 Steady State Conditions Inside and Outside an Industry Cluster

We now turn to deriving steady state H-type firm employment and profits in a cluster and in dispersed regions. In the clustered region and in all dispersed regions, it must be the case in steady state that worker flows out of the L industry balance flows into the L industry. Letting e denote the employment rate in the L industry, this implies $\lambda Me = \delta(1-e)M$, which gives us the following steady state condition:

$$e = \delta/(\delta + \lambda)$$

Let $l^u(w| p)$ denote the steady state number of workers employed at a wage less than or equal to w at an H-type with productivity p in an unclustered region and let $l^c(w| p)$ denote the steady state number in the clustered region. Hence, $l^u(p\text{-}c| p)$ denotes total employment at an H-type firm with productivity p in an unclustered region (a firm in an unclustered area will never pay more than $p\text{-}c$ to a worker) and $l^c(p| p)$ denotes total employment for a firm with productivity p in the cluster.[45]

In an isolated region, an H-type firm employs labor such that $l^u(p\text{-}c| p) = l^u(b| p)$ for all $p \in [p_{min}, p_{max}]$. Hence, equating inflows and outflows of workers at the firm, $\delta l^u(b| p) = \lambda eM$, which implies that in equilibrium,[46]

$$l^u(b| p) = \lambda M/(\delta + \lambda) = l^u$$

In a cluster, there is more than one H-type firm ($1 < N \leq N^W$) and wages vary within each firm. A worker employed at a clustered H-type firm with productivity p at a wage w could separate either exogenously (at a rate δ) or because he or she receives an offer from another H-type firm with productivity $p^r > p$. Setting outflows equal to inflows for the stock of workers employed at all H-type firms with productivity less than p in the cluster yields

$$(\delta + \gamma[1 - F(p)])N\int_{p_{min}}^{p} l^c(x|x)dF(x) = \lambda eMF(p)$$

Differentiating this expression with respect to p yields an expression for $l^c(p| p)$:

$$l^c(p| p) = [(\delta + \gamma)\lambda\delta M)/[(\delta + \lambda)N]\ [1/(\delta + \gamma[1 - F(p)])^2]$$

Unlike l^u, which does not vary with p, $l^c(p| p)$ depends on p as well as the number of firms in the cluster and other parameters of the model.[47] Current operating profits in an isolated area, in which an H type firm

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[45] That is, $l^u(p) = \int_{w'_0(p)}^{p-c} dl^u(x|p)$ and $l^c(p) = \int_{w'_0(p)}^{p} dl^c(x|p)$.

[46] Of course, this expression for l^u is equivalent to $(1\text{-}e)M$.

[47] Setting $\gamma=0$, the expression for $l^c(p| p)$ collapses to that of l^u when $N=1$.

must pay a recurring productivity cost per worker of c, sets wages equal to b, and employs l^u workers, are given by $\pi^u(p)$:

$$\pi^u(p) = (p - c - b)l^u$$

Substituting in for l^u we arrive at a final expression for current operating profits for an unclustered firm,

$$\pi^u(p) = [(p - c - b)\lambda M]/(\delta + \lambda)$$

which are linearly increasing in p:

$$\partial\pi^u(p)/\partial p = \lambda M/(\delta + \lambda)$$

In a cluster, given that the lowest a worker can earn in an H-type with productivity p is $w'_0(p)$ and that the highest is p, current operating profits $\pi^c(p)$ for a firm with p that locates in a cluster are

$$\pi^c(p) = \int_{w'_0(p)}^{p} (p - w)dl^c(w \mid p)$$

Integrating by parts yields

$$\pi^c(p) = [(p - w)l^c(w|p)|_{w'(p)}^{p}] + \int_{w'_0(p)}^{p} l^c(w|p)dw$$

Canceling terms and noting that $l^c(w| p) = l^c(q(w, p)| q(w, p))$, we have

$$\pi^c(p) = \int_{w'_0(p)}^{p} l^c(q(w, p)|q(w, p))dw$$

Note that differentiating the expression for $q(w, p)$ with respect to w yields

$$\partial q(w, p)/\partial w = 1 - [\gamma/(\rho + \delta)]\{[1 - F(q(w, p))]\partial q(w, p)/\partial w\}$$

Rearranging terms,

$$\partial q(w, p)/\partial w = 1/\{1 + [\gamma/(\rho + \delta)][1 - F(q(w, p))]\}$$

We can substitute this into $\pi^c(p)$ to arrive at the following expression for operating profits:

$$\pi^c(p) = \int_b^p \{1 + [\gamma/(\rho + \delta)][1 - F(x)]\}\, l^c(x| x)dx$$

Plugging in for $l^c(x| x)$ in the expression for current operating profits among H-type firms in a clustered region yields[48]

$$\pi^c(p) = \{[(\delta+\gamma)\lambda\delta M]/[(\delta + \lambda)(\rho + \delta)N]\} \int_b^p [\{\rho + \delta + \gamma[1 - F(x)]\} / \{\delta + \gamma[1 - F(x)]\}^2]dx$$

[48] Intuitively, in the case in which there is no on-the-job search in the H industry ($\gamma = 0$), operating profits collapse to

$$\pi^c(p) = [(p-b)\lambda M]/[(\delta + \lambda)N]$$

which mirrors the situation in a dispersed region.

For a given N, applying Leibniz's rule, one finds that profits are increasing in p.

$$\partial\pi^c(p)/\partial p = \{[(\delta + \gamma)\lambda\delta M]/[(\delta + \lambda)(\rho + \delta)N]\} \\ [\{\rho + \delta + \gamma[1-F(p)]\}/\{\delta + \gamma[1-F(p)]\}^2] > 0$$

Differentiating with respect to p again, one finds that profits in a cluster are increasing at an increasing rate (noting that $\partial F(p)/\partial p > 0$).

$$\partial\pi^{c2}(p)/\partial p^2 = \{[(\delta + \gamma)\lambda\delta M]/[(\delta + \lambda)(\rho + \delta)N]\} \\ [\gamma[\partial F(p)/\partial p]\{2\rho + \delta + \gamma[1-F(p)]\}] \ / \{\delta + \gamma[1-F(p)]\}^3 > 0$$

The convexity of $\pi^c(p)$ reflects the fact that higher productivity firms that cluster have higher profits per worker and can accumulate more workers. That is, there is a size effect that arises in a cluster that amplifies the per-worker productivity advantage of having a higher p.[49]

A.4 The Spatial Distribution of Firms

An H-type with a given p compares steady state $\pi^c(p)$ and $\pi^u(p)$ and determines, taking N as given, whether to cluster. In equilibrium, those firms that cluster have productivities such that $\pi^c(p) > \pi^u(p)$; i.e., such that

$$\{[(\delta+\gamma)\lambda\delta]/[(\delta + \lambda)(\rho + \delta)N]\} \\ \int_b^p [\ \{\rho + \delta + \gamma[1 - F(x)]\} \ / \{\delta + \gamma[1 - F(x)]\}^2\ ]dx > [(p - c - b)\lambda]/(\delta + \lambda)$$

Depending on parameter values, we could have several equilibrium scenarios. To pin down more results, we assume that $F(p)$ is uniform. Letting $k = \{[(\delta+\gamma)\lambda\delta M]/[(\delta + \lambda)(\rho + \delta)N]\}$, we then have

$$\pi^c(p) = k\int_b^p [\rho/\{\delta + \gamma[(p_{max}-x)/(p_{max}-b)]\}^2]dx + k\int_b^p [1/\{\delta + \gamma[(p_{max}-x)/(p_{max}-b)]\}]dx$$

Integrating this expression gives us

$$\pi^c(p) \quad = k[\rho(p-b)(p_{max}-b)] \ / \{[(\delta+\gamma p_{max})(p_{max}-b) - \gamma p][(\delta+\gamma p_{max})(p_{max}-b) - \gamma b]\} \\ - k[(p_{max}-b)/\gamma]\ \{log[(\gamma(p_{max}-p) + \delta(p_{max}-b))/((\gamma+ \delta)(p_{max}-b))]\}$$

In this case, taking the derivative of profits with respect to p yields

$$\partial\pi^c(p)/\partial p = \ [k\rho(p_{max}-b)^2] \ / \{[(\gamma(p_{max}-p) + \delta(p_{max}-b)]^2\} \\ + [k(p_{max}-b)] \ / \ [(\gamma(p_{max}-p) + \delta(p_{max}-b)] > 0$$

and the second derivative is

$$\partial\pi^{c2}(p)/\partial p^2 = \ [2k\gamma\rho(p_{max}-b)^2] \ / \{[(\gamma(p_{max}-p) + \delta(p_{max}-b)]^3\} \\ + [k\gamma(p_{max}-b)] \ / \{[(\gamma(p_{max}-p) + \delta(p_{max}-b)]^{\ 2}\} > 0$$

---

[49] Let $\hat{w}^u(p)$ denote the average wage at an unclustered firm with productivity p and $\hat{w}^c(p)$ denote the average wage at a clustered firm with productivity p. Clearly, $\hat{w}^u(p) = b$ for all $p \in [p_{min}, p_{max}]$. In a cluster, however, $\hat{w}^c(p) = [pl^c(p|\ p) - \pi^c(p)]/l^c(p|\ p)$. So long as $p - \pi^c(p)/l^c(p|\ p) > b$, then, $\hat{w}^c(p) > \hat{w}^u(p)$.

Hence, when F is uniform, profits in a cluster are increasing at an increasing rate in p, starting at zero where $p=b$ and rising to a maximum of

$$\pi^c(p_{max}) = [k(p_{max}-b)]\ \{\rho/[\delta(\gamma + \delta)] + (1/\gamma)\log[((\gamma + \delta)/\delta]\}$$

or, substituting in for k,

$$\pi^c(p_{max}) = (p_{max}-b)\ \{[(\delta+\gamma)\lambda\delta M]/[N(\delta + \lambda)(\rho + \delta)]\}\ \{\ \rho/[\delta(\gamma + \delta)] + (1/\gamma)\log[((\gamma + \delta)/\delta]\ \}$$

Using this expression for $\pi^c(p)$ and the expression for $\pi^u(p)$, we can analyze several possible equilibrium outcomes.[50]

[Figure A.2: The Spatial Distribution of Firms in the H Industry]

All firms cluster if c is sufficiently high and the distribution of productivity is such that p_{max} is less than p_1. Clearly, a firm with $p = b$ would find it preferable to cluster (in which case profits are zero) as opposed to disperse (in which case profits are negative). A firm with $p = p_{max}$ would also find it optimal to cluster so long as

$$c > (p_{max} - p_{min})[1 - J\ \{[\delta(\delta+\gamma)]/[(\rho + \delta)N]\}] \text{ for } 1 \leq N \leq N^W$$

where $J = \{\rho/[\delta(\gamma + \delta)] + (1/\gamma)\log[((\gamma + \delta)/\delta]\}$. In words, no firm under this condition is productive enough to find it optimal to locate alone and bear the productivity disadvantage associated with isolation; firms' profits are always greater in a cluster than outside a cluster despite the poaching that occurs in an agglomeration of establishments. In this case, there is no truncation in the productivity distribution in the cluster, as all firms locate in one region and the full range of p from b to p_{max} is represented there.

On the other hand, if $b < p_1 < p_{max} < p_2$, only low productivity firms cluster when $c > 0$. Again, a firm with $p = b$ would find it preferable to cluster and earn zero profits than to disperse and earn negative profits. Consider a firm with $p = p_1$, which would have profits in isolation of

$$\pi^u(p_1) = [(p_1 - c - b)\lambda M]/(\delta + \lambda)$$

and profits in a cluster of

$$\pi^c(p_1) = k[\rho(p_1-b)(p_1-b)]\ /\ \{[(\delta+\gamma\ p_1)(p_1-b) - \gamma p_1][(\delta+\gamma\ p_1)(\ p_1-b) - \gamma b]\}$$
$$- k[(p_1-b)/\gamma]\ \{\log[(\gamma(p_1-p) + \delta(p_1-b))/((\gamma+ \delta)(\ p_1-b))]\}$$

since the maximum p represented in the cluster is no longer p_{max} but instead is p_1. That is, in this instance, the distribution of p in the cluster is truncated from above, with H-type firms with $p < p_1$ clustering while

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[50] In the case in which $c = 0$, or when there is no productivity advantage associated with locating in a cluster, the only dynamically consistent equilibrium solution is one in which all firms disperse. Suppose that some firms cluster and some disperse. The least productive firm among those that cluster, whose productivity we denote p_0 (where $p_0 \leq p_{max}$), will be incapable of poaching from other H-type firms but will be the victim of poaching by other H-type firms. Profits for the least productive firm in the cluster will be

$$\pi^c(p_0) = \{\lambda\delta M/[(\delta + \lambda)(\rho + \delta)N]\}\ [(\rho + \delta + \gamma)\ /(\delta + \gamma)](p_0 - b)$$

If $c = 0$, then $\pi^c(p_0) < \pi^u(p_0) = [(p_0 - b)\lambda M]/(\delta + \lambda)$ if $\rho > 0$ and

$$N > [\delta(\rho + \gamma + \delta)]/[(\rho + \delta)(\ \gamma + \delta)]$$

which implies, since $[\delta(\rho + \gamma + \delta)]/[(\rho + \delta)(\ \gamma + \delta)] < 1$ and as long as some on-the-job search occurs ($\gamma > 0$), that any $N > 1$ will make it more profitable to disperse than to cluster.

those with $p > p_1$ dispersing. In equilibrium, profits for those firms that cluster in this case must be greater than those associated with isolating given the dearth of higher productivity firms present to poach workers. At p_1, $\pi^c(p_1) = \pi^u(p_1)$, which implies

$$\{[(\delta+\gamma)\delta]/[(\rho + \delta)N]\} [\rho(p_1-b)^2] / \{[(\delta+\gamma p_1)(p_1-b) - \gamma p_1][(\delta+\gamma p_1)(p_1-b) - \gamma b]\} - (p_1 - c - b) = 0$$

which defines for a given c a number $N \leq N^W$ firms that cluster in equilibrium and a number $N^W - N$ that disperse. A firm with $p \in [b, p_1)$ in this case would find it in its best interest to cluster, whereas a firm with $p \in (p_1, p_{max}]$ would find it optimal to isolate. Taking total derivatives, given a positive denominator in the first term in the expression above, one can show that the number of firms that cluster is increasing in c.[51]

[51] I leave to future work a closer examination of the final case of $p_{max} > p_2$. In this case, a firm with $p = b$ would again prefer to cluster and earn zero profits than to disperse and earn negative profits. A firm with productivity p would, as before, have profits in isolation of

$$\pi^u(p) = [(p - c - b)\lambda M]/(\delta + \lambda)$$

Yet each firm in a cluster would face a partitioned distribution of productivities, which complicates derivations of steady state conditions.

Appendix 2

This appendix provides additional information regarding the data I use in this study. As I note in the text, I take advantage of employee-employer matched data for one large U.S. state for the third quarter of 1991 through the third quarter of 2003. I chose the sample state based on its size, its representativeness, the relatively long time span of its data, and the quality of the geographic coding of its establishments. That said, geographic coding in my dataset is not perfect. Roughly 85%-90% of sample establishments have rooftop-confident geographic coordinates (latitude and longitude), the most precise coordinates possible. About 95% of establishments have coordinates that are accurate at least at the Census tract level, and 98% have coordinates that are accurate at least the county level.[52] For the purposes of examining agglomeration patterns, I use only establishments that are precisely geographically coded.[53] This ensures a consistent sample of establishments for the measures of clustering I construct. For multi-unit SEINs, I use only those units that are precisely coded; others are dropped from the analysis.[54]

Table A.1 presents statistics on sample establishments and jobs.[55]

[Table A.1: Descriptive Statistics]

The average size of software establishments in the sample increased over the sample period, as did mean real ($1997) annualized earnings within establishments. The average fraction of establishments' workforces that were male inched slightly higher during the decade, while the average fraction of establishments' workforces that were white edged lower. Though remaining high compared to many other sectors at over two years of college, the average of mean within-establishment educational attainment levels declined over the sample period, possibly because establishments in the sample grew larger and took on additional administrative staff.

Consistent with the statistics aggregated to the establishment level, the descriptive statistics for jobs reveal that males comprised a high and rising share of workers in the industry and whites a declining share. Further, the average age of workers on the job in the industry rose over the decade, while the average educational attainment level slipped somewhat. Average annualized real earnings, however, rose markedly between the early 1990s and the early 2000s.

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[52] See http://www.census.gov/geo/www/census2k.html for information on Census geographic identifiers.

[53] I experimented with using more inclusive samples of establishments (including those assigned to block, tract, or county centroids), comparing results with those obtained using only the sample of establishments for which we have only rooftop coordinates. On the whole, the aggregate results were little changed, though there was some evidence that "heaping" of establishments in geographic centroids sometimes biased clustering statistics upward and resulted in spurious patterns of co-location. Hence, throughout the analysis, I use the sample of establishments for which we have accurate rooftop address information. It is worth noting, however, that the sample of rooftop-confident establishments is not a random sample of units. In general, the quality of addresses for establishments in rural regions, establishments in slower-growing areas, and establishments that are part of larger multi-unit firms tends to be worse. See Freedman et al. (2006) for further details.

[54] Ideally, my sample would cover as many states as possible. Although I corroborated my results with four additional states separately, the computational requirements of pooling individual and establishment-level panel data across multiple states are considerable.

[55] Employment and earnings figures include only individuals who are full-quarter workers, or workers who are observed at a given establishment in periods t-1, t, and t+1. This measure largely eliminates from the sample workers employed only part of a quarter, and hence whose reported earnings represent compensation for an indeterminate amount of time (anywhere from one to 90 days).

References

Abowd, John M., Fredrik Andersson, Kevin McKinney, Marc Roemer, Bryce Stephens, Lars Vilhuber, and Simon Woodcock. "The LEHD Infrastructure Files and the Creation of the Quarterly Workforce Indicators." LEHD Technical User Guide. 2005.

Almeida, Paul and Bruce Kogut. "Localization of Knowledge and the Mobility of Engineers in Regional Networks." *Management Science.* 45(7). 1999.

Andersson, Fredrik, Simon Burgess, and Julia Lane. "Cities, Matching and the Productivity Gains from Agglomeration." *Journal of Urban Economics*. Forthcoming. 2006.

Arrow, K. J. "Economic Welfare and the Allocation of Resources for Invention." *The Rate and Direction and Inventive Activity: Economic and Social Factors.* Ed. R.R. Nelson. NBER Special Conference Series. 13. Princeton, NJ: Princeton UP. 1962.

Audretsch, David B. and Maryann P. Feldman. "R&D Spillovers and the Geography of Innovation and Production." *American Economic Review*. 86(3). 1996.

Bank, David. "Borland Suit Says Microsoft Lured Workers." *Wall Street Journal*. A.3. May 8, 1997.

Brown, Charles and James Medoff. "The Employer Size-Wage Effect." *Journal of Political Economy.* 97(5). 1989.

Burdett, Kenneth and Dale Mortensen. "Wage Differentials, Employer Size and Unemployment." *International Economic Review*. 39(2). 1998.

Boudette, Neal E. and Ann Davis. "SAP Suit to Protect Intellectual Property To Test Support for New Legal Theory." *Wall Street Journal.* A1. December 29, 1999.

Combes, Pierre-Philippe and Gilles Duranton. "Labor Pooling, Labor Poaching, and Spatial Clustering." *Regional Science and Urban Economics*. 36(1). 2006.

Costa, Dora L. and Matthew E. Kahn. "Power Couples: Changes in the Locational Choice of the College Educated, 1940-1990." *Quarterly Journal of Economics*. 115(4). 2000.

David, Paul A. and Joshua L. Rosenbloom. "Marshallian Factor Market Externalities and the Dynamics of Industrial Localization." *Journal of Urban Economics.*28(3). 1990.

Davis, Donald R. and David E. Weinstein. "Economic Geography and Regional Production Structure: An Empirical Investigation." *European Economic Review*. 43(2). 1999.

Davis, Steven J. and John C. Haltiwanger. *Job Creation and Destruction.* Cambridge, MA: MIT UP. 1996.

Dumais, Guy, Glenn Ellison, and Edward L. Glaeser. "Geographic Concentration as a Dynamic Process." *Review of Economic Statistics*. 84(2). 2002.

Duranton, Gilles and Henry G. Overman. "Testing for Localization Using Micro-Geographic Data." *Review of Economic Studies.* 72(4). October 2005.

Duranton, Gilles and Diego Puga. "Micro-Foundations of Urban Agglomeration Economies." Eds. J. Vernon Henderson and Jacques-François Thisse. *Handbook of Regional and Urban Economics*. 4. Amsterdam: North Holland. 2004.

Eberts, Randall and Edward Montgomery. "Cyclical versus Secular Movements in Employment Creation and Destruction." NBER Working Paper 5162. 1995.

Ellison, Glenn and Edward L. Glaeser. "Geographic Concentration in U.S. Manufacturing Industries: A Dartboard Approach." *Journal of Political Economy.* 105(5). 1997.

____. "The Geographic Concentration of Industry: Does Natural Advantage Explain Agglomeration?" *American Economic Review*. 89(2). 1999.

Ethier, Wilfred E. "National and International Returns to Scale in the Modern Theory of International Trade." *American Economic Review*. 72(3): 389-405. 1982.

Faberman, R. Jason. "Job Flows and Establishment Characteristics: Variations across Metropolitan Areas." William Davidson Institute Working Paper No. 609. 2003.

Fallick, Bruce, Charles A. Fleischmann, and James B. Rebitzer. "Job Hopping in Silicon Valley: Some Evidence Concerning the Micro-Foundations of A High Technology Cluster." NBER Working Paper 11710. 2005.

Freedman, Matthew L. "Measuring Clustering Within and Between Industries: A Distance-Based Approach." University of Maryland-College Park. Mimeo. 2006.

Fujita, Masahisa and Hideaki Ogawa. "Multiple Equilibria and Structural Transition of Non-Monocentric Urban Configurations." *Regional Science and Urban Economics.* 12(2). 1982.

Fujita, Masahisa, Paul R. Krugman, and Anthony J. Venebles. *The Spatial Economy: Cities, Regions, and International Trade*. Cambridge: MIT Press. 1999.

Glaeser, Edward L. "Learning in Cities." *Journal of Urban Economics*. 46(2): 254-277. 1999.

Greene, William H. *Econometric Analysis.* 5th Edition. Upper Saddle River, NJ: Prentice Hall. 2003.

Haltiwanger, John C., Julia Lane, and James Spletzer. "Wages, Productivity, and the Dynamic Interaction of Businesses and Workers." NBER Working Paper No. 7994. 2000.

Helsley, Robert W., and William C. Strange. "Matching and Agglomeration Economies in a System of Cities." *Regional Science and Urban Economics.* 20(2). 1990.

Holmes, Thomas J. "Localization of Industry and Vertical Disintegration." *Review of Economics and Statistics*. 81(2). 1999.

Holmes, Thomas J. and John J. Stevens. "Geographic Concentration and Establishment Scale." *Review of Economics and Statistics.* 84(4). 2002.

Jaffe, Adam B., Manuel Trajtenberg, and Rebecca Henderson. "Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations." *Quarterly Journal of Economics*. 108(3). 1993.

Jovanovic, Boyan and Rafael Rob. "The Growth and Diffusion of Knowledge." *Review of Economic Studies*. 56(4). 1989.

Jovanovic, Boyan and Yaw Nyarko. "The Transfer of Human Capital." *Journal of Economic Dynamics and Control*. 19(5-7). 1995.

Justman, Moshe. "The Effect of Local Demand on Industry Location." *The Review of Economics and Statistics*. 76(4). 1994.

Kim, Sunwoong. "Labor Heterogeneity, Wage Bargaining, and Agglomeration Economies." *Journal of Urban Economics*. 28(2). 1990.

____. "Heterogeneity of the Labor Market and City Size in an Open Spatial Economy." *Regional Science and Urban Economics*. 21(1). 1991.

Kim, Sukkoo. "Expansion of Markets and the Geographic Distribution of Economic Activities: The Trends in U.S. Regional Manufacturing Structure, 1860-1987." *Quarterly Journal of Economics*. 110(4). 1995.

Krugman, Paul R. "Increasing Returns and Economic Geography." *Journal of Political Economy.* 99(3): 483-99. June 1991.

Marshall, Alfred. *Principles of Economics.* London: Macmillan. 1920 (orig. 1890).

Møen, Jarle. "Is Mobility of Technical Personnel a Source of R&D Spillovers?" *Journal of Labor Economics*. 23(1). 2005.

Pakes, Ariel and Shmuel Nitzan. "Optimum Contracts for Research Personnel, Research Employment, and the Establishment of "Rival" Enterprises." *Journal of Labor Economics*. 1(4). 345-65. 1983.

Porter, Michael E. *The Competitive Advantage of Nations*. New York: Macmillan. 1990.

Postel-Vinay, Fabien and Jean-Marc Robin. "Equilibrium Wage Dispersion with Worker and Employer Heterogeniety." *Econometrica*. 70(6). 2002.

Richards, Bill. "Informix Charges Oracle 'Pirated' Engineering Team." *Wall Street Journal.* B7. January 27, 1997.

Richtel, Matt. "Microsoft Sues Over Google's Hiring of a Former Executive." *New York Times*. Business/Financial Desk. July 20, 2005.

Rosen, Sherwin. "Learning and Experience in the Labor Market." *Journal of Human Resources*. 7(3). 1972.

Rosenthal, Stuart S. and William C. Strange. "The Determinants of Agglomeration." *Journal of Urban Economics.* 50(2): 191-229. September 2001.

____. "Geography, Industrial Organization, and Agglomeration." *Review of Economics and Statistics.* 85(2): 377-93. May 2003.

Rotemberg, Julio J. and Garth Saloner. "Competition and Human Capital Accumulation: A Theory of Interregional Specialization and Trade." *Regional Science and Urban Economics*. 30(4). 2000.

Salop, Steven C. "Monopolistic Competition with Outside Goods." *Bell Journal of Economics*. 10(1). 1979.

Saxenian, Annalee. *Regional Advantage: Culture and Competition in Silicon Valley and Route 128.* Cambridge, MA: Harvard UP. 1994.

Stevens, David W. "Employment That Is Not Covered by State Unemployment." LEHD Technical Paper No. TP-2002-16. January 2002.

U.S. Department of Agriculture. "National Resources Inventory: 2001 Annual NRI." National Resources Conservation Service. 2001. http://www.nrcs.usda.gov/technical/land/nri01/

U.S. Government Accountability Office. "Offshoring: U.S. Semiconductor and Software Industries Increasingly Produce in China and India." GAO-06-423. 2006. http://www.gao.gov/new.items/d06423.pdf

Wheeler, Christopher H. "Search, Sorting, and Urban Agglomeration." *Journal of Labor Economics*. 19(4). 2001.

Table 1: Establishment-Specific Location Quotients for Selected Years

	1992Q2		1998Q2		2003Q2	
Establishments	822		1,020		882	
	Mean	SD	Mean	SD	Mean	SD
Establishment-Based						
5-Mile Radius	2.29	1.95	2.15	1.66	2.07	1.61
10-Mile Radius	2.02	1.49	1.98	1.41	1.90	1.35
25-Mile Radius	1.53	0.89	1.67	1.04	1.60	0.97
50-Mile Radius	1.38	0.65	1.47	0.75	1.40	0.69
Share Clustered at 25 Miles	0.63	0.48	0.63	0.48	0.59	0.49
Employment-Weighted						
5-Mile Radius	2.22	1.98	2.52	4.19	2.92	5.09
10-Mile Radius	2.03	1.71	2.23	2.81	2.51	3.58
25-Mile Radius	1.63	1.24	1.93	1.59	2.06	1.83
50-Mile Radius	1.46	0.89	1.66	1.16	1.63	1.18
Share Clustered at 25 Miles	0.59	0.49	0.52	0.50	0.50	0.50

Table 2: Discrete-Time Proportional Hazard Models

	Employment-Based Location Quotient		
	All	Unclustered	Clustered
Clustering Indicator (0/1)	0.0747		
	(0.0172)***		
Log Annualized Earnings ($1997)	-1.5634	-1.3311	-1.6170
	(0.0643)***	(0.0702)***	(0.0461)***
Log Annualized Earnings Squared	0.0612	0.0499	0.0634
	(0.0029)***	(0.0034)***	(0.0021)***
Log Establishment Employment (FQ)	-0.0231	0.0668	-0.0553
	(0.0094)**	(0.0162)***	(0.0103)***
Log Establishment Employment Squared	-0.0087	-0.0186	-0.0057
	(0.0010)***	(0.0019)***	(0.0011)***
Observed Prior Experience in 5112 (0/1)	0.2078	0.1574	0.2240
	(0.0112)***	(0.0209)***	(0.0131)***
Age (Years)	-0.0015	-0.0075	0.0008
	(0.0025)	(0.0036)**	(0.0029)
Age Squared	0.0000	0.0001	0.0000
	(0.0000)	(0.0000)*	(0.0000)
Male	0.0104	0.0003	0.0199
	(0.0069)	(0.0120)	(0.0082)**
White	0.1126	0.0863	0.1210
	(0.0069)***	(0.0126)***	(0.0081)***
Education 12-15 Years	-0.0158	-0.0361	-0.0033
	(0.0122)	(0.0197)*	(0.0147)
Education 16+ Years	-0.0293	-0.0446	-0.0220
	(0.0125)**	(0.0206)**	(0.0150)
Constant	5.9313	4.9510	6.1758
	(0.6781)***	(0.8292)***	(1.0386)***
County Dummies	Yes	Yes	Yes
Observations (Job x Quarter)	1249964	400222	849742

Robust standard errors clustered on person in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 3: Multinomial Logit Model

	Employment-Based Location Quotient	
	Transition within Industry	Transition Out of Sample
	(Relative to Transition to Different Industry)	
Clustering Indicator (0/1)	0.3312	-0.0666
	(0.0581)***	(0.0358)*
Observed Tenure in Current Job (Quarters)	0.0325	-0.0049
	(0.0059)***	(0.0033)
Observed Tenure in Current Job Squared	-0.0007	0.0005
	(0.0003)***	(0.0001)***
Log Annualized Earnings ($1997)	1.7490	-0.2581
	(0.2374)***	(0.0642)***
Log Annualized Earnings Squared	-0.0669	0.0126
	(0.0106)***	(0.0031)***
Log Establishment Employment (FQ)	0.2842	-0.2899
	(0.0342)***	(0.0176)***
Log Establishment Employment Squared	-0.0226	0.0323
	(0.0035)***	(0.0019)***
Observed Prior Experience in 5112 (0/1)	0.4770	-0.2070
	(0.0353)***	(0.0268)***
Age (Years)	-0.0010	-0.1053
	(0.0089)	(0.0050)***
Age Squared	-0.0002	0.0015
	(0.0001)	(0.0001)***
Male (0/1)	0.0903	-0.1245
	(0.0237)***	(0.0148)***
White (0/1)	0.0505	0.1589
	(0.0238)**	(0.0154)***
Education 12-15 Years (0/1)	-0.0305	0.1610
	(0.0424)	(0.0277)***
Education 16+ Years (0/1)	-0.0114	0.2642
	(0.0433)	(0.0285)***
Constant	-14.4538	1.5035
	(1.3093)***	(0.3587)***
Year and Quarter Dummies	Yes	
County Dummies	Yes	
Left Censoring Dummies (Interacted)	Yes	
Observations	130,127	

Robust standard errors clustered on person in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 4: Earnings Consequences of Job Transitions into Industry

Transitions into Software from Other Industry	Employment-Based Clustering Index
→ Clustered Software Establishment (0/1)	-0.0202
	(0.0062)***
Change in (Log) Establishment Employment	0.0600
	(0.0023)***
Change in (Log) Establishment Employment Squared	0.0013
	(0.0004)***
Change in Age	-0.0192
	(0.0136)
Change in Age Squared	0.0083
	(0.0015)***
Change County Dummy	0.0239
	(0.0053)***
Constant	0.6964
	(0.1250)***
Separation Year and Quarter Dummies	Yes
Accession Year and Quarter Dummies	Yes
Observations	106,564

Treatment selection model (not shown) regresses → clustered software establishment dummy on worker age at start of new job, worker age squared at start of new job, worker age at end of prior job, worker age squared at end of prior job, worker gender, worker race, worker education, new establishment (log) employment, new establishment (log) employment squared, prior establishment (log) employment, prior establishment (log) employment squared, new establishment county dummies, prior establishment county dummies, separation year and quarter dummies, and accession year and quarter dummies.

Robust standard errors clustered on person in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 5: Worker-Level Panel Earnings Regressions

	Employment-Based Location Quotient		
	Fixed Effects	Random Effects	Pooled OLS [1]
Location Quotient (LQ)	0.0671	0.0537	0.0683
	(0.0171)***	(0.0111)***	(0.0123)***
LQ Squared	-0.0074	-0.0044	-0.0062
	(0.0026)***	(0.0018)**	(0.0020)***
Observed Tenure in Current Job (Quarters)	0.0096	0.0086	0.0158
	(0.0012)***	(0.0006)***	(0.0011)***
Observed Tenure in Current Job Squared	-0.0002	-0.0001	-0.0003
	(0.0000)***	(0.0000)***	(0.0000)***
LQ x Tenure	0.0013	0.0017	0.0020
	(0.0007)*	(0.0007)**	(0.0011)*
LQ x Tenure Squared	-0.0000	-0.0001	-0.0000
	(0.0000)	(0.0000)***	(0.0000)
LQ Squared x Tenure	-0.0002	-0.0003	-0.0005
	(0.0001)	(0.0001)**	(0.0002)**
LQ Squared x Tenure Squared	0.0000	0.0000	0.0000
	(0.0000)*	(0.0000)***	(0.0000)
Observed Prior Experience in 5112 (0/1)		0.1113	0.0950
		(0.0147)***	(0.0161)***
LQ x Observed Prior Experience in 5112	0.0226	0.0714	0.0765
	(0.0861)	(0.0135)***	(0.0150)***
LQ Squared x Observed Prior Experience in 5112	-0.0087	-0.0133	-0.0144
	(0.0104)	(0.0026)***	(0.0029)***
Log Establishment Employment (FQ)	0.0717	0.0966	0.1450
	(0.0071)***	(0.0050)***	(0.0057)***
Log Establishment Employment Squared	0.0013	-0.0025	-0.0089
	(0.0007)*	(0.0005)***	(0.0006)***
Age (Years)	0.1184	0.1191	0.1139
	(0.0050)***	(0.0017)***	(0.0020)***
Age Squared	-0.0012	-0.0013	-0.0012
	(0.0000)***	(0.0000)***	(0.0000)***
Male (0/1)		0.3077	0.3217
		(0.0029)***	(0.0036)***
White (0/1)		0.0944	0.1047
		(0.0030)***	(0.0037)***
Education 12-15 Years (0/1)		0.1093	0.0983
		(0.0057)***	(0.0067)***
Education 16+ Years (0/1)		0.2765	0.2541
		(0.0059)***	(0.0068)***
Constant	7.8461	7.2099	7.2201
	(0.1591)***	(0.0381)***	(0.0437)***
Year and Quarter Dummies	Yes	Yes	Yes
County Dummies	Yes	Yes	Yes
Left Censoring Dummies (Interacted)	Yes	Yes	Yes
Observations	1522806	1522806	1522806
R-squared	0.14		0.31
Number of Groups (Jobs)	170196	170196	

Standard errors clustered on job in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

[1] Included as a basis for comparison and robustness check

Table A.1: Descriptive Statistics

	1992Q2		1998Q2		2003Q2	
Establishments	822		1,020		882	
	Mean	SD	Mean	SD	Mean	SD
Employment	20.38	54.03	29.62	131.99	45.76	161.75
Share Male	0.64	0.26	0.68	0.26	0.69	0.26
Share White	0.77	0.27	0.72	0.30	0.65	0.31
Average Age	36.47	6.37	38.45	7.07	40.62	7.50
Average Education	15.32	1.45	14.38	1.60	14.25	1.57
Average Annualized Earnings ($1997)	54,441	41,901	61,804	39,988	67,510	48,006
Job Spells	19,234		35,943		40,364	
	Mean	SD	Mean	SD	Mean	SD
Share Male	0.61	0.49	0.63	0.48	0.65	0.48
Share White	0.75	0.44	0.67	0.47	0.58	0.49
Age	35.02	8.98	36.43	9.22	37.72	9.15
Education	15.36	2.46	14.39	2.82	14.16	2.94
Average Annualized Earnings ($1997)	61,392	88,452	78,051	225,753	97,302	381,870

Figure 1:
Average Number of Establishments and Employment
within Selected Radii
NAICS 5112

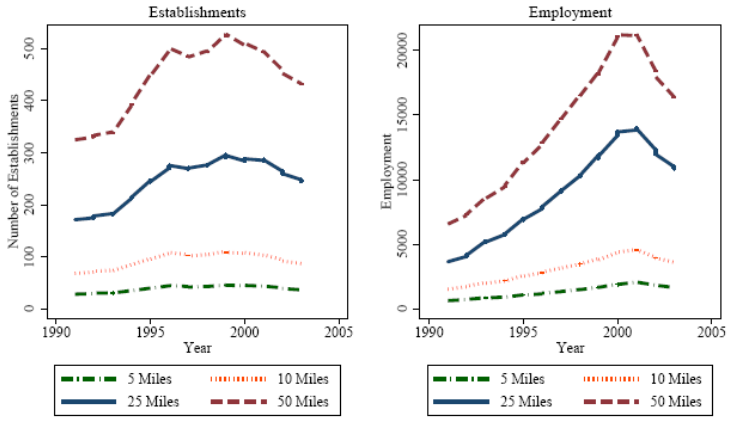
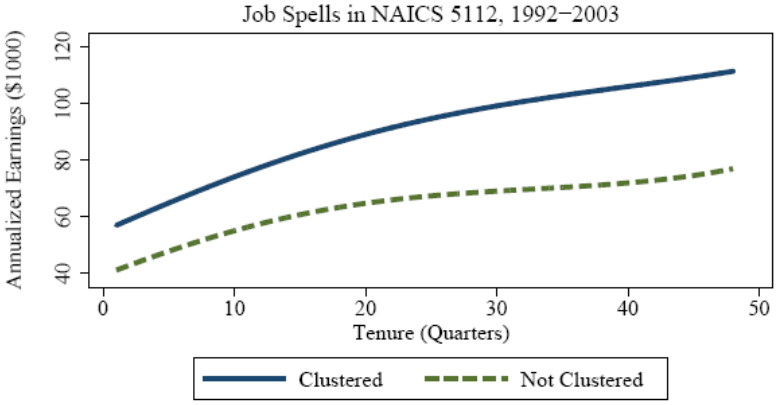


Figure 2:
Earnings−Tenure Profiles
in Clustered and Unclustered Establishments
Job Spells in NAICS 5112, 1992−2003

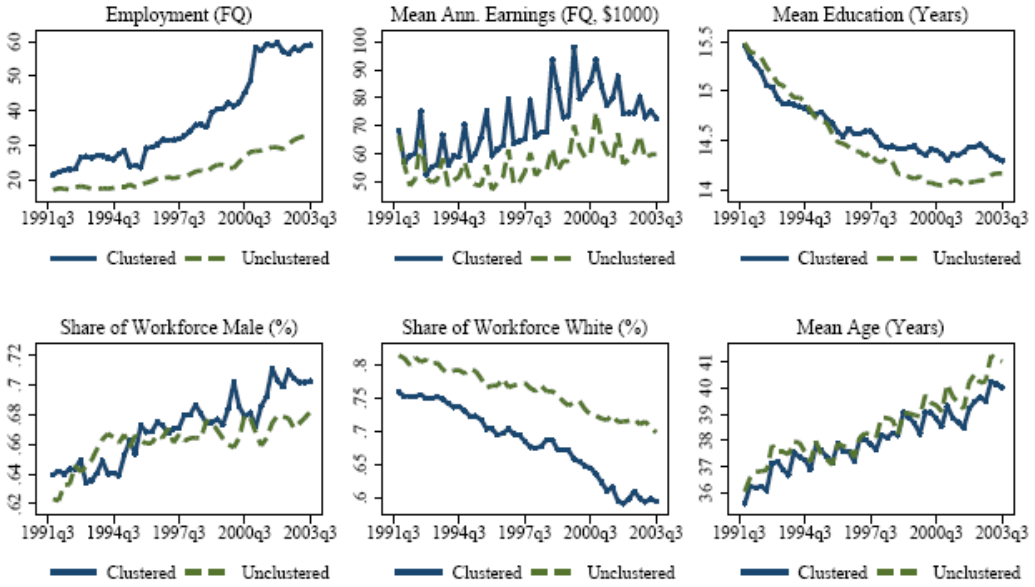


Includes job spells in NAICS 5112 that are not left censored. Jobs in clustered establishments (of which there are 102023, with 93528 unique workers employed in 1354 unique establishments) represent spells in establishments with LQs greater than or equal to one a majority of the time that the job exists. Jobs in unclustered establishments (49921, with 47277 unique workers employed in 1099 unique establishments) represent spells in establishments with LQs less than one a majority of the time that the job exists.

Figure 3:

Workforce Characteristics of Clustered and Unclustered Establishments

NAICS 5112, 1991–2003



Employment–based location quotients for establishments in NAICS 5112.

Figure A.1: Possible Outcomes of Bertrand Competition

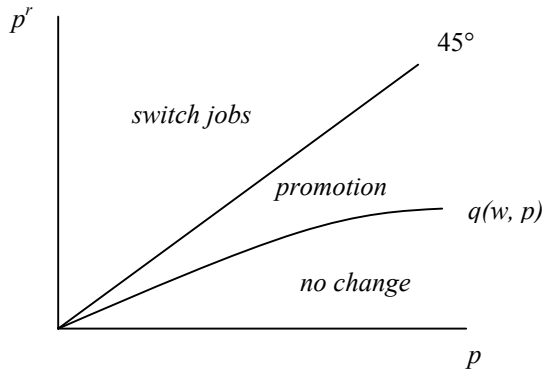
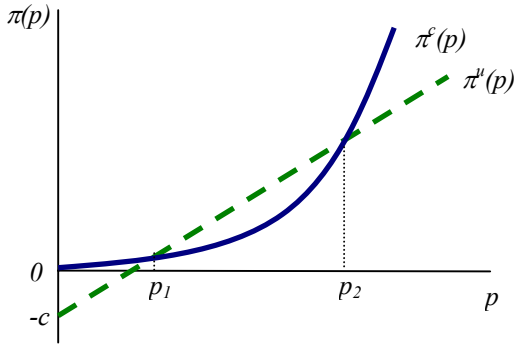



Figure A.2: The Spatial Distribution of Firms in the H Industry