ABSTRACT

Title of dissertation: LOCATION CHOICE, PRODUCT CHOICE, AND THE HUMAN RESOURCE PRACTICES OF FIRMS

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This thesis is comprised of three chapters. The first investigates the implications of industrial clustering for labor mobility and earnings dynamics. 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 software publishing 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.

While the first chapter reveals striking relationships between the human resource practices and location decisions of high-technology establishments, the second chapter (joint with F. Andersson, J. Haltiwanger, J. Lane, and K. Shaw) draws key connections between the hiring and compensation policies of innovative firms and the nature of their product markets. We show that software firms that operate in product markets with

highly skewed returns to innovation pay a premium to attract talented workers. Yet these same firms also reward loyalty; that is, highly skilled workers faithful to their employers enjoy higher earnings in firms with a greater variance in potential payoffs from innovation. These results not only contribute to our knowledge of firm human resource practices and product market strategies, but also shed light on patterns of income inequality within and between industries.

Building on this final idea, the last chapter (joint with F. Andersson, E. Davis, J. Lane, B. McCall, and L. Sandusky) examines the contribution of worker and firm reallocation to within-industry changes in earnings inequality. We find that the entry and exit of firms and the sorting of workers and firms based on worker skills are key determinants of changes in industry earnings distributions over time. However, the importance of these and other factors in driving observed dynamics in earnings inequality varies across sectors, with aggregate shifts often disguising fundamental differences in the underlying forces effecting change.

LOCATION CHOICE, PRODUCT CHOICE, AND THE HUMAN RESOURCE PRACTICES OF FIRMS

by

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PREFACE

This document reports the results of research and analysis undertaken by the U.S. Census Bureau staff. It has undergone a Census Bureau review more limited in scope than that given to official Census Bureau publications. This research is a part of the U.S. Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) Program, which is partially supported by the National Science Foundation Grants SES-9978093 and SES-0427889 to Cornell University (Cornell Institute for Social and Economic Research), the National Institute on Aging Grant R01~AG018854-02, and the Alfred P. Sloan Foundation. The views expressed on statistical, methodological, and technical issues are those of the author(s) and not necessarily those of the U.S. Census Bureau, its program sponsors, or its data providers.

Some of the data used in this dissertation are confidential data from the LEHD Program. The U.S. Census Bureau supports external researchers' use of these data through the Research Data Centers (http://www.ces.census.gov). For questions regarding the data, please contact Jeremy S. Wu, Program Manager, U.S. Census Bureau, LEHD Program, Attn: Holly Brown, Room 6H136C, 4600 Silver Hill Road, Suitland, Maryland 20746, USA (did.local.employment.dynamics@census.gov, http://lehd.did.census.gov).

DEDICATION

This dissertation is dedicated to my parents, Glenn and Sara Freedman,

and

to Emily Owens.

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I would like to express my deepest gratitude to the members of my dissertation committee for their encouragement and advice. This research also benefited greatly from helpful comments from staff at the LEHD Program at the U.S. Census Bureau.

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Job Hopping, Earnings Dynamics, and Industrial Agglomeration*

1.1 Introduction

Over a quarter of the nation's workers in the software publishing industry are located in one state, and nearly a third of that state's software publishing workers are employed in a single county.[1] Though one of the most prominent examples of industrial clustering, software is not the only sector in which it occurs; evidence suggests that firms in a number of industries, from automobile manufacturing to biotechnology, concentrate 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; Ellison and Glaeser 1997, 1999).

Clustering by firms in particular industries could influence local labor market dynamics by facilitating the pooling of skilled labor and by fostering competition over workers. Employing new data and novel measures of concentration, this chapter examines the nature and extent of industrial clustering and explores how agglomeration among establishments affects labor mobility, earnings levels, and earnings growth rates in one high-technology sector in which the availability of skilled workers is of prime importance. I develop a model of on-the-job search that features a spatial dimension and industry-specific skills. The model explains how variation in labor market outcomes across clustered and dispersed establishments could stem from the strategic interaction of

* The author gratefully acknowledges guidance and helpful comments from John Haltiwanger, John Shea, Michael Pries, and Fredrik Andersson. The author also thanks staff at the U.S. Census Bureau's LEHD Program and Center for Economic Studies as well as participants at the University of Maryland macroeconomics seminar series and the 2006 Society of Labor Economists Conference for comments on earlier versions of this work.

[1] Author's calculations based on publicly available County Business Patterns data for 2004.

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.

Consistent with the model, an empirical analysis using rich longitudinal employee-employer matched data reveals that geographic clustering among establishments in the software publishing industry is associated with shorter job durations and greater job-hopping among individuals within the sector. Moreover, relative to those employed by firms in more isolated locations, workers in regions with greater clustering generally enjoy stronger within-job earnings growth. However, workers in clusters reap these higher returns to tenure only after making implicit investments through lower wages early in their careers.

The chapter proceeds as follows. The next section reviews literature on industrial clustering, labor pooling, and job and earnings mobility. Section 1.3 develops a theoretical framework to analyze industrial agglomeration and local labor market dynamics. Section 1.4 describes the data, discusses the methodology I employ to measure clustering, and presents basic descriptive statistics. Section 1.5 turns to the empirical analysis, and Section 1.6 concludes.

1.2 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.[2] Though each explanation has some substantiating evidence,[3] this chapter focuses on the labor market as the source of incentives for firms to cluster or disperse.

Labor pooling, or the accumulation of individuals with specific skills near a cluster of similar firms, 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 locate in close geographic proximity.

One strand of the agglomeration 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. Technological spillovers arise when one firm benefits from another's research and development activities without sharing in the costs. To the extent that workers can carry their acquired skills and technical know-how from

[2] For models in which 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, see Fujita and Ogawa (1982), Jovanovic and Rob (1989), Jovanovic and Nyarko (1995), and Glaeser (1999). For labor pooling models, see Salop (1979), Kim (1990, 1991), Helsley and Strange (1990), and Duranton and Puga (2004).

[3] 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 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. (2007).

job to job, labor mobility within a particular geographic area could facilitate productivity-enhancing knowledge transfers (Saxenian 1994, Almeida and Kogut 1999, Fallick et al. 2006, 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.[4] Firms could lure workers from other businesses by offering superior earnings prospects, although threatened firms could also counter potential poaching by raising wages for their own employees. 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).

A number of researchers have documented relatively high rates of job mobility among workers in different clusters of high-technology firms, and several have noted that job-hopping could act as a source of agglomeration economies (Angel 1989, Saxenian 1994, Fallick et al. 2006). However, the broader ramifications of clustering in particular industries for earnings dynamics are not as well explored. Some classes of job search models make predictions about not only job mobility patterns, but also individuals' earnings-tenure profiles and wage variation within and between firms. Augmented with a spatial dimension and industry-specific skills, a model of on-the-job search yields insights into clustering's potential implications for important labor market outcomes, implications that previous literature has not addressed.

[4] In addition to its labor market effects, clustering clearly fosters 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). In their location decisions, firms must weigh both labor and product market considerations. This chapter focuses on the software publishing industry, for which product market considerations are likely of second-order importance in driving location choice since software is sold primarily in a national market or even an international market and uses few material inputs.

1.3 Model

To motivate the subsequent analysis, I briefly outline in this section a theoretical model that highlights the tension between labor pooling and poaching by considering the strategic interaction of firms as they compete over workers. In the model, which I describe in greater detail in Appendix A, workers continually search for new opportunities to boost lifetime earnings and firms that value sector-specific skills make offers and counteroffers to attract knowledgeable employees in an industry cluster. The model can account for the fact (documented below) that agglomeration among high-technology establishments 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 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 extends the on-the-job search models of Burdett and Mortensen (1998) and Postel-Vinay and Robin (2002a, 2002b) by incorporating a spatial dimension and industry-specific skills. Firms in a high-technology industry that are geographically clustered can tap into a pool of skilled labor but also face the risk of having their employees lured away by nearby firms in the same sector that can offer more attractive earnings prospects. High-technology firms that are isolated, on the other hand, do not have access to skilled workers, but face no risk that other similar firms will poach their employees. Operating in an environment of perfect information, firms pay each of their workers no more than the amount required to prevent them from quitting for another job. However, due to heterogeneous firm productivity, workers in a cluster may experience both within-job wage growth, which arises 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.

1.3.1 Setup

There exist two industries, one comprised of low-technology firms (L) and the other 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 of an infinite number of locations. Firms in the H industry have constant returns to labor but are heterogeneous in their productivity p, which has CDF F over $[p_{min}, p_{max}]$. 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. Isolated regions contain L-type firms and at most one H-type firm.

There is a working population of fixed size M in all locations. While workers can move without cost between jobs within a region, I assume that the cost of moving among regions is prohibitively high (or, equivalently, that the cost for firms to hire from other regions is prohibitively high).[5] Workers have a discount rate $\rho > 0$ and linear flow utility

[5] Although the geographic immobility of workers represents a strong assumption, this chapter aims to explain localized job flows and earnings dynamics conditional on the spatial distribution of economic activity. The immobility assumption turns out only to be relevant in obtaining the model's main results to the extent that workers cannot have the option of relocating to the clustered region from an isolated one and vice versa; workers will have no incentive to move between isolated 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

$u(x) = x$. 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 is otherwise subtracted from productivity; that is, whereas a firm with productivity p paying a wage w in a cluster earns profits of p-w, an identical firm outside a cluster earns profits of p-c-w.[6] This productivity differential in favor of labor in clustered firms could stem from local workers' 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]

In each location, H-type firms make take-it-or-leave-it offers to workers, who search on the job in both sectors. L-industry workers receive offers from firms in the H-industry at a rate λ and H-industry workers receive offers from other H-type firms in the region at a rate γ. An individual's wage 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, I assume a random matching technology such that, conditional on getting an offer from an H-type firm, workers in both the L industry and the H industry receive

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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 software publishing (NAICS 5112) for another in the same industry, of the 71% of workers who begin in a clustered establishment, 87% end up at a clustered establishment (where I define "clustered" using a employment-based location quotient with a radius of 25 miles, a measure I describe later in the chapter). Conversely, of the 29% who begin in an isolated establishment, 69% remain in an isolated establishment when they change jobs within the sector. Additionally, the average physical distance between employers for job hoppers in my sample is 16.6 miles, and for over half of job hoppers it is fewer than 12 miles.

[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.

[7] For industries in which input-output linkages are relatively important, such a productivity advantage could stem from reduced transportation costs or improved access to consumer markets. See Appendix A for further discussion of the nature of the productivity differential.

offers from every other H-type firm in the same location with equal probability.[8] 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 addition to endogenous separations due to poaching, H-industry workers in all locations are separated from their jobs at an exogenous rate δ, in which case they immediately obtain jobs in the L industry. There is no unemployment.

1.3.2 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 firm that promises more in present value than earning b forever. When a worker at an H-type firm in a cluster receives an offer from another H-type firm, 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 each firm places an upper bound on how much it would be willing to pay to retain or poach her.

Importantly, as I describe in greater detail below, a worker's wage need not be bid all the way up to the productivity level of the "loser" of the competition, as individuals will be willing to accept lower wages to work at higher productivity firms that can offer superior long-term earnings prospects. When faced with competition over scarce labor, more productive firms have the ability to grant greater future wage increases and hence provide more favorable career earnings prospects. Therefore, in anticipation of higher

[8] The assumption of random matching, or that all H-type firms have an equal probability of being sampled, implies that the productivity distribution and the sampling distribution of H-type firms are identical. Alternative matching technologies include balanced matching, in which case the sampling probability is proportional to firm employment, and some mixture of random and balanced matching (Burdett and Vishwanath 1988, Mortensen and Vishwanath 1994).

future earnings, workers, and in particular those at the top end of the wage distribution at low productivity firms, will under some circumstances consent to wage cuts to move to better firms.

To be more specific, when a "rival" H-type firm with productivity p^r meets a worker earning a wage w at another H-type firm with productivity p, 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 for the worker at her current employer (where $q(w, p) \leq p$). If the rival firm's productivity is such that $p^r \leq q(w, p)$, the worker's wage and employment status will not change as a result of the encounter. In this case, the rival firm cannot profitably offer the worker a wage that she would find preferable to her current employment situation.

A second possibility is that $q(w, p) < p^r \leq p$, in which case the rival firm can make an attractive offer that still guarantees it will earn positive rents on the worker. However, since the productivity of each firm places an upper bound on how much it would be willing to pay to employ the worker, and since $p^r \leq p$, the worker's wage in this case will be bid up within her current firm to $w'(p^r, p)$, precisely the level that renders that worker indifferent between staying with her employer and hopping to the rival firm. 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.[9] Finally, if $p < p^r$, the challenging firm can successfully lure the worker away from her current employer, as the rival can extend

[9] 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 her current employer.

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.

Leaving the derivation to Appendix A, 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. A firm extending an offer cares not what the worker is currently earning, but rather the maximum that the incumbent firm could offer and that the worker would accept to stay in her current job. 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; 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 thus in some cases, depending on her wage history within a firm, a worker might accept a wage cut to move to an employer in which she expects stronger wage growth. Lastly, the higher the arrival rate or the lower the separation rate, the lower the wage offer required to poach a given employee.

Intuitively, one can derive a similar equation for the offer made to a worker in the L industry who is earning b (again, see Appendix A for details):

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

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 in the H industry induces a worker to accept an initial cut in compensation to escape from the L sector; in a sense, a worker is willing to "pay" to get 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.

1.3.3 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. An H-type firm in an isolated region that meets a worker in the L industry will make the lowest possible wage offer to hire the worker, just as it would in a cluster. That offer must provide a value equal to the opportunity cost of employment in industry L. In a remote location, though, the lack of other H-type firms competing over workers implies $\gamma = 0$. Therefore, as I explain more formally in Appendix A, 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 workers derive equal utility from working in the L and H industries outside an industry cluster.

1.3.4 Job Hopping and Earnings Dynamics

As this chapter specifically aims to characterize the consequences of clustering for worker job mobility and earnings dynamics, I refrain from a lengthy formal derivation of its implications for firm location decisions. Instead, 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 high-technology 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: **Job durations in the H industry will be shorter inside a cluster than outside a cluster.**

A worker in the H industry outside a cluster separates from a job only at the exogenously given separation rate δ, whereas a worker in a cluster separates at the separation rate δ plus the probability of being contacted by another H-type firm with productivity greater than p, $\gamma[1 - F(x)]$. The likelihood that a worker will exit a clustered H-type firm is therefore decreasing in the productivity of that worker'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 the H industry will be more prevalent inside a cluster than outside a cluster.**

Given the immobility of workers across locations in the model, the likelihood that an individual in an isolated region 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 an H-type firm with productivity p will transition to another H-type firm equals $\gamma[1 - F(p)]$, which is positive for $p < p_{max}$. A worker's willingness to job hop within the sector depends on whether a prospective employer can promise larger wage gains over the long run than her 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.

Prediction 3: **Workers moving from outside the H industry into a clustered H-type firm will accept earnings discounts relative to workers moving into an isolated H-type firm.**

An H-type firm that meets a worker in the L industry need only offer a wage that makes the worker indifferent between taking the job and continuing to work in the L industry. In general, this wage is lower in a cluster of H-type firms, where a job in the H industry offers opportunities for advancement; indeed, the prospect of higher future wages due to competition among firms can induce a worker in a cluster to accept a pay cut to enter the H industry. In an isolated area, 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. Moreover, to the extent that it might drive up the arrival rate, greater clustering would increase the magnitude of the initial pay cut that workers are willing to accept to enter the H industry.

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

The likelihood of receiving a pay increase at an isolated establishment is zero regardless of its productivity; 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. Meanwhile, competition among firms that cluster acts to drive up earnings levels within each firm. The probability that a clustered firm with productivity p rewards a promotion to a worker earning w is $\gamma[F(p) - F(q(w, p))]$, which implies that the likelihood of receiving a pay raise in a given firm is the greatest for workers with the lowest current wages. On the other hand, 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.[10]

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 in the model. Due to the strategic interaction of firms, workers in clusters enjoy upward-sloping, concave wage-tenure profiles and benefit from past industry experience in securing jobs with good earnings prospects. 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

[10] Conditional on the current employer's productivity, job 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.

productive ones due to poaching.[11] Meanwhile, job and earnings mobility are depressed in remote locations due to the lack of opportunities for on-the-job search and poaching. In contrast to conditions in a cluster, intra-firm wage dispersion is absent and workers face flat earnings-tenure profiles.[12]

1.4 Data

1.4.1 Sources

To test the predictions of the model, I require a data set that combines information about workers and their employers and that permits me to track each over a long time span. Due to incomplete information about individuals' employment and earnings histories, small sample sizes, and reporting problems, traditional survey data render it difficult to measure job mobility or to evaluate the temporal pattern of earnings changes among workers (Bound and Krueger 1991, Bound et al. 2001, Roemer 2002, Stinson 2002, Abowd et al. 2006). I study the impact of industrial agglomeration on local labor market dynamics using a new employee-employer matched data set constructed and maintained by the U.S. Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) Program. LEHD integrates quarterly administrative earnings information for workers derived from U.S. state unemployment insurance (UI) records with internal

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[11] 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.

[12] It is worth noting 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 one isolated area will pay the same wages as a less productive firm that locates in another 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. 2007).

Census Bureau censuses and surveys.[13] The result is a database that is particularly well suited to examining job mobility and earnings dynamics and that provides an opportunity to explore clustering's impact on local labor markets more extensively than have past studies.

LEHD data boast several advantages over household and business based survey data. The data are current and relatively accurate because businesses face financial penalties for misreporting their workers' employment and earnings information. Since the scope of the quarterly longitudinal data is nearly the full universe of firms and workers, I can follow individuals over time as they move across the earnings distribution and across employers. Additionally, the integrated records contain information on workers' demographic characteristics, including date of birth, race, sex, and education. Though sparse relative to the information on individuals in surveys such as the Current Population Survey and Panel Study of Income Dynamics, the worker characteristics on the LEHD data permit some flexibility in investigating variation across demographic groups and serve as important controls in the empirical analysis. Critically for this study, LEHD data also contain a detailed industry classification code (six-digit NAICS) and a unique address, including latitude/longitude coordinates, for nearly all establishments.

The LEHD data 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.[14] Second, there is spotty coverage of workers and firms in some sectors, including

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[13] More extensive descriptions of LEHD data appear in Abowd et al. (2005) and Haltiwanger et al. (2007).
[14] As of late 2006, 43 states (including the District of Columbia) are participating in the LEHD Program. 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.

agriculture, non-profits, and public administration.[15] 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 LEHD impute some measures of workforce composition and earnings for the small number of establishments that are part of larger multi-unit operations,[16] it is nevertheless possible to pinpoint individual establishments within multi-unit SEINs geographically without resorting to imputation using LEHD data.[17]

1.4.2 Sample

In this chapter, I focus on establishments and workers in the software publishing industry (NAICS 5112).[18] The software industry has been the subject of a large body of research on clustering and is a natural candidate for studying how labor mobility interacts with agglomeration (Saxenian 1994, Fallick et al. 2006). Products in the software publishing 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

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[15] See Stevens (2002) for a more detailed description of the LEHD database coverage issues.

[16] Fewer than 10% of establishments in the sample are part of multi-unit operations, though close to one-fourth of workers in the sample are employed in establishments that are part of multi-unit operations.

[17] 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 does LEHD have information on precisely which individuals are employed at each SEIN unit, though the geographic location of each SEIN unit and its total employment are known. 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.

[18] The Census Bureau defines NAICS 5112 as consisting of "establishments primarily engaged in computer software publishing or publishing and reproduction. Establishments in this industry carry out operations necessary for producing and distributing computer software, such as designing, providing documentation, assisting in installation, and providing support services to software purchasers. These establishments may design, develop, and publish, or publish only." See http://www.census.gov/naics for details.

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 suggests that labor poaching aimed at appropriating valuable knowledge from rivals occurs and represents a legitimate concern among firms in the industry.[19]

For this study, I use data for one large U.S. state for the third quarter of 1991 through the third quarter of 2003. I selected 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. I extract from the statewide data the complete employment and earnings histories of all individuals observed to work at least one full quarter in software, where being full quarter employed at time t requires a worker have positive earnings at a given establishment in periods $t-1$, t, and $t+1$. This 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).

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 as well as descriptive statistics appear in Appendix B, but several features of the workers and firms in the sample are

[19] 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).

worth noting. The industry's workforce is about two-thirds male and one-third non-white. Software workers, who generally have at least some college education, enjoyed substantial real earnings gains on average as the industry expanded in the 1990s. Earnings dispersion also rose sharply over the course of the decade. Meanwhile, software firms have grown larger on average, though after rising steadily in the 1990s, the total number of establishments in the industry has declined in recent years in the sample state.

1.4.3 Measuring Clustering

Researchers have long recognized that it is critical to control for the general spatial distribution of economic activity when measuring industrial clustering. However, most measures of clustering rely on coarse areal data that aggregate establishments to counties, metropolitan statistical areas, states, or other spatial zones (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 facing a given establishment, 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.[20]

I adapt the conventional location quotient (LQ) measure to examine the extent of clustering at the establishment level.[21] The LQ is a measure of an industry's level of concentration around a particular location over and above what one would expect in light of the general spatial distribution of economic activity. Typically, the LQ is computed as

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

the ratio of an industry's share of total establishments or employment in a "local" area, such as a county, relative to its share of total establishments or employment in a larger area, such as the nation. As a refinement on the conventional measure, I take advantage of the rich geographic information on my dataset and construct establishment-specific LQs 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 LQ 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 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. Values of the LQ exceeding one reflect higher than average concentration at a particular location; values less than one indicate less than average concentration.

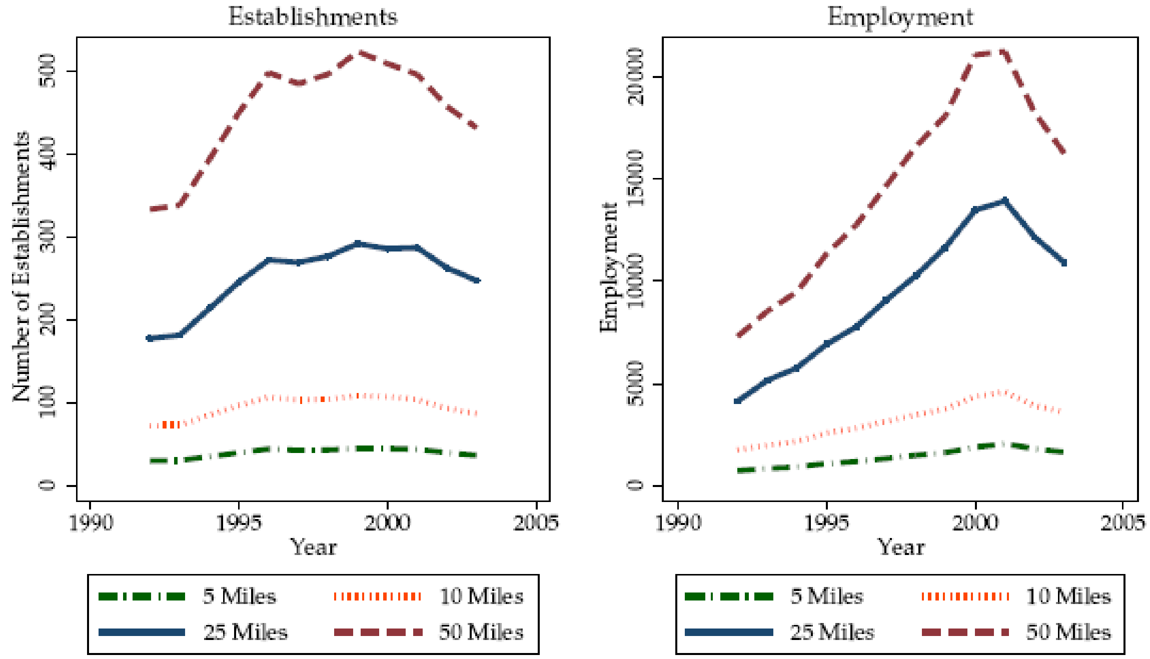
This methodology provides for each establishment a single measure of agglomeration that reflects the extent to which that establishment is more or less clustered than is typical for all businesses. For example, a software establishment with a large number of other software establishments or workers nearby will not have a LQ greater than one unless it is the case that software is overrepresented in the immediate vicinity compared to economic activity more generally. Importantly, and in contrast with the more traditional LQ measure, the measure I construct can be applied at a variety of different spatial scales that need not be dictated by administrative boundaries,[22] and it permits a closer evaluation of how clustering relates to other outcomes within a particular industry.

1.4.4 Descriptive Statistics

In this section, I present basic descriptive statistics on the nature and extent of agglomeration in the software publishing industry in the sample state. Figure 1.1 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.

[22] 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.

Figure 1.1: Average Number of Software Establishments and Employment within Selected Radii
NAICS 5112, 1991-2003



Based on LEHD data.

Throughout much of the 1990s, the number of other software establishments and workers located close to sample establishments climbed, reaching a plateau later in the sample period and retreating somewhat after 2000. While informative, this reveals little about whether establishments in the industry grew more or less clustered relative to the broader spatial distribution of economic activity.

The LQ sheds light on the degree of clustering over and above what one would expect given the general distribution of economic activity. Table 1.1 presents clustering statistics for software establishments in the sample over different distances for selected years.

Table 1.1: Establishment-Specific Location Quotients for the Software Industry in Selected Periods

Means and Standard Deviations

	1992Q2		1998Q2		2003Q2	
(a) Establishment-Based						
Number of Establishments	822		1,020		882	
	Mean	SD	Mean	SD	Mean	SD
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	1.9	1.35
25-Mile Radius	1.53	0.89	1.67	1.04	1.6	0.97
50-Mile Radius	1.38	0.65	1.47	0.75	1.4	0.69
Share Clustered at 25 Miles	0.63	0.48	0.63	0.48	0.59	0.49
(b) Employment-Based						
	1992Q2		1998Q2		2003Q2	
Number of Establishments	822		1,020		882	
	Mean	SD	Mean	SD	Mean	SD
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	0.5	0.5	0.5

Based on LEHD data.

Establishment-specific LQs, whether measured using neighboring establishments or employment, are on average well above one in the software industry for circles with radii of up to at least 50 miles. While average LQs have declined modestly over time on an establishment basis in the software industry, employment-weighted LQs rose on average between the early 1990s and early 2000s. In other words, employment in the industry has grown increasingly concentrated, though establishments have not.

Compared to other four-digit NAICS industries, economic activity in the software sector is quite clustered taking into account to the broader spatial distribution of economic activity. Table 1.2 presents for 2003Q2 employment-based LQs using a 25-mile radius for several selected industries. I chose some of these industries, such as nonmetallic mineral mining (NAICS 2123) and department stores (NAICS 4521), based on their representativeness of the broader set of industries within their general industry category, while I selected others, such as apparel knitting mills (NAICS 3131) and pharmaceutical and medicine manufacturing (NAICS 3254), because they have served as the subject of much prior research into clustering.

Table 1.2: Establishment-Specific Location Quotients for Selected Industries
2003Q2
Employment Based, 25-Mile Radius

Industry (NAICS)	Mean	SD
Nonmetallic Mineral Mining (2123)	3.18	22.64
Apparel Knitting Mills (3131)	1.82	0.98
Aerospace Product and Parts Manufacturing (3364)	1.66	1.03
Communications Equipment Manufacturing (3342)	1.65	1.34
Scientific Research and Development Services (5417)	1.55	1.23
Steel Product Manufacturing (3312)	1.34	1.38
Pharmaceutical and Medicine Manufacturing (3254)	1.28	0.76
Radio and Television Broadcasting (5151)	1.18	0.69
Securities & Commodity Contracts Brokerage (5231)	1.16	1.04
Department Stores (4521)	1.06	0.46
Junior Colleges (6112)	0.83	0.39

Based on LEHD data.

Although there is a clear tendency toward clustering in the software industry, it is not the case that all activity in the sector is concentrated in a few locations. Indeed, as Table 1.1 reveals, at a 25-mile radius, only 59% of sample establishments had an establishment-based LQ greater than one in 2003; for the employment-based measure, this figure was 50%.

The histogram in Figure 1.2 depicts the distribution of values of the employment-based LQ measured with a radius of 25 miles across software establishments in the second quarter of 2003. The figure reinforces the message that, while a large percentage of software establishments are clustered, there exists substantial variation in LQ values across businesses in the sample. Heterogeneity in the extent of clustering among software establishments constitutes the source of variation that permits me to identify relationships between clustering in the industry and particular labor market outcomes below.

Figure 1.2: Histogram of Establishment-Specific LQs for Software Establishments
NAICS 5112, 2003Q2

Based on LEHD data.

1.5 Empirical Analysis

In this section, I turn to an empirical analysis of how establishment clustering affects job mobility and earnings patterns in the software publishing industry. Testing each of the main predictions of the model in Section 1.3 with a reduced-form approach, I examine first industrial clustering's effects on job duration and then its implications for job-hopping within versus between industries. Next, I evaluate whether workers who obtain jobs in agglomerated software establishments accept lower starting wages, and finally I assess whether workers in clusters enjoy faster subsequent wage growth and steeper earnings-tenure profiles.

1.5.1 Job Mobility

I begin my analysis of job mobility by identifying individual separations from software industry jobs, which I do by comparing worker and establishment matches in consecutive quarters in the data. A separation in quarter *t* occurs when a worker is full quarter employed at an establishment at *t* but not at *t+1*. The quarterly separation rate in the data averages 7%, slightly lower than estimates for the broader economy of close to 10% by Abowd and Zellner (1985) and Shimer (2005) but not surprising given the age, gender, and educational profile of workers in software. The restriction that individuals in the sample be employed for a full quarter at each employer also eliminates workers with very transient spells in the industry.[23]

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

[23] Firm exit could be responsible for observed worker separations. However, the worker separation rate is over twice the rate of firm exit in NAICS 5112. The average quarterly firm exit rate in the sample is 3.2%.
[24] Of the workers who leave NAICS 5112 for another industry, 59% stay within NAICS 5 (28% of all private-sector workers in the U.S. economy are employed in NAICS 5 according to the 2002 Economic Census), 16% go to NAICS 4 (22%), 14% to NAICS 3 (13%), and 4% to NAICS 6 (14%). The remaining 7% transition to jobs in other industries.

be due to a right-censored spell of unemployment, withdrawal from the labor force, or a move to another state.

The quarterly frequency of the data, together with the full quarter employment restriction, makes it difficult to assess accurately the incidence of direct job-to-job flows versus job-to-job flows with intervening spells of unemployment.[25] Because I do not observe non-employment spells that last less than one quarter except in the razor-edge case in which a worker transitions between jobs right between quarters, I define a direct job-to-job transition as one involving one quarter or less of non-employment (i.e., no observed attachment to any firm) between jobs for the purposes of the empirical analysis. Roughly 46% of job transitions between software and different industries and 49% of job transitions within software occur with one quarter or less of intervening non-employment.

Empirical Test of Prediction 1: **Job durations in the H industry 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 her current job, controlling for a host of worker and establishment characteristics. I use a panel that pools 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 a discrete-time hazard model of the probability that a worker i is observed to separate from establishment j after

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

τ quarters, conditional on not having separated until that time. The discrete-time hazard rate, $h_{ij\tau}$, is given by

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

where T_{ij} is a discrete random variable representing the quarter in which job spell ij ends; C_{ij} represents a job-specific, time-invariant indicator for clustering equal to one if establishment j has an employment-weighted LQ greater than or equal to one in the majority of the quarters over which the spell ij is observed;[26] $\boldsymbol{X}_{it}$ is a vector of characteristics for worker i at time t that includes a quadratic in the natural log of real ($1997) annualized earnings and a quadratic in age as well as dummies for prior industry experience, gender, race, and education; $\boldsymbol{Z}_{jt}$ is a vector of characteristics for establishment j at t that includes a quadratic in the natural log of employment, an urban density variable (calculated as the share of total sample employment across all industries within a circle with a radius of 25 miles of the establishment at t), and a dummy for county; and η_t is a dummy for year and quarter.[27] I include time dummies to control for the influence of cyclical macroeconomic factors, while I include county dummies to control for the impact of differences across counties such as variation in infrastructure quality and industry composition. A logistic re-parameterization of the hazard is

[26] Here as well as in the remainder of the empirical analysis I use an employment-based LQ calculated using a 25-mile radius. In my sample, 88% of workers who job-hop within the industry transition to a new establishment that is fewer than 25 miles away from their old establishment. By comparison, 38% job hop to a new establishment that is fewer than five miles away from their old establishment, and 62% hop to one that is fewer than ten miles away. Also, while for ease of exposition I use a time-invariant indicator for clustering, the results are robust to using instead the continuous, time-varying LQ measure (entering either linearly or as a quadratic). They are also robust to using a clustering indicator defined using radii fewer than 25 miles and defined using the average LQ over the spell.

[27] Note that τ, the number of quarters a spell lasts, is distinct from t, the calendar date associated with worker and firm characteristics and the time dummies.

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

such that

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

where, in my preferred specification, the baseline hazard $\zeta(\tau)$ consists of dummy variables for each period in which the worker is at risk of separating (corresponding to the length of the job spell in quarters).[28] In contrast to continuous-time versions of survival models that assume a non-constant hazard (for example, the Weibull), the discrete-time model can capture non-monotonic changes in the baseline hazard. I assume there exists no unobserved heterogeneity and estimate the model using maximum likelihood. A single individual in the sample can potentially separate more than once from different software jobs, and since unobserved characteristics of each person are likely to be correlated over time, I correct standard errors by clustering on person.[29]

The theoretical model implies that the coefficient β should be positive and significant, and the results from the discrete-time proportional hazard model, which I present in Table 1.3, confirm that this is the case. The point estimates indicate that, controlling for other worker and firm characteristics, clustering in the software industry is

[28] 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 I present from the more flexible specification outlined in the text.

[29] If I allow for arbitrary correlation within counties or tracts over time instead of within workers, the precision of my estimates declines slightly, though the coefficients of interest maintain the same significance levels.

associated with abbreviated job spells. The implied odds ratio suggests that being employed at a clustered software establishment increases the likelihood of separating by 13% relative to being employed at an establishment that is not clustered. This statistically and economically significant effect comes on top of the impact of being in an economically dense location; the effect of urbanization is captured in the urban density coefficient, which is also positive and significant.

The impact of clustering on job duration is robust to the inclusion of controls for earnings and employer size, each of which bears negatively on the probability of separation. Beyond possessing prior experience in the software industry, being male, and being white, which all tend to boost one's likelihood of separating, the influence of other worker demographic characteristics on the probability of leaving a software firm are muted after taking into account earnings, firm size, and characteristics of the local area.

Overall, while the results of the hazard model 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. I now turn to a deeper analysis of these outcomes.

Table 1.3: Factors Affecting the Probability of Separation from Software Industry Jobs
Discrete-Time Proportional Hazard Model

Clustering Indicator (0/1)	0.1266
	(0.0180)***
Log Annualized Earnings ($1997)	-1.522
	(0.0657)***
Log Annualized Earnings Squared	0.0580
	(0.0030)***
Urban Density	0.6618
	(0.1126)***
Log Establishment Employment (FQ)	-0.0355
	(0.0080)***
Log Establishment Employment Squared	-0.008
	(0.0010)***
Observed Prior Experience in 5112 (0/1)	0.1977
	(0.0112)***
Age (Years)	-0.0003
	(0.0025)
Age Squared	0.0000
	(0.0000)
Male	0.0184
	(0.0069)***
White	0.1288
	(0.0070)***
Education 12-15 Years	-0.0029
	(0.0122)
Education 16+ Years	-0.0037
	(0.0125)
Constant	5.9975
	(0.6724)***
Observations (Job x Quarter)	1,249,964

Controls include year and quarter dummies and county dummies. Sample excludes left-censored jobs. Standard errors in parentheses allow for arbitrary correlation over time within the same person.
* significant at 10%; ** significant at 5%; *** significant at 1%. Based on LEHD data.

Empirical Test of Prediction 2: **Job-hopping within the H 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 affects one's likelihood of taking a job with another establishment in the same industry as opposed to moving 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 the characteristics of the worker and the establishment from which she separates.

Let S = *{Transition to Same Industry Directly, Transition to Same Industry with Intervening Non-employment, Transition to Different Industry Directly, Transition to Different Industry with Intervening Non-employment, 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 out of the sample. The probability of transitioning from a software job to any of the other four states can be expressed as follows:

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

k = Transition to Same Industry Directly, Transition to Same Industry with Intervening Non-employment, Transition to Different Industry Directly, Transition to Different Industry with Intervening Non-employment

where C_{jt} represents a dummy for whether establishment j is clustered at the time of worker i's separation t; $\boldsymbol{X}_{it}$ is a vector of individual-level covariates for worker i at the time of separation t that includes a quadratic in tenure and a quadratic in log real annualized earnings as well as dummies for prior industry experience, gender, race, and education; $\boldsymbol{Z}_{jt}$ is a vector of establishment-level covariates at the time of separation t that includes a quadratic in log employment and urban density; and η_t is a time dummy. β^k and the vectors $\boldsymbol{\Phi}^k$ and $\boldsymbol{\Omega}^k$ are coefficients affecting the likelihood of transitioning to future work status $k \in S$. The number of separations from software firms that I observe in the data is relatively small at just over 130,000, and 13% of those separations are from left-censored software job spells. Therefore, to maximize sample size, I include in the multinomial logit estimation sample workers with left-censored job spells in software and incorporate a dummy for left censoring that I interact with terms subject to such censoring (in particular, tenure and tenure squared). I again cluster the errors on person since individuals in the sample may separate from more than one software job.[30]

[30] 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 I cannot reject the null hypothesis that the odds of one outcome occurring are independent of other alternatives. Wald tests for combining outcome categories also 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. This holds in all specifications regardless of the radius chosen for the LQ and regardless of whether the LQ is establishment-based versus employment-based.

The log odds estimates from the multinomial logit that I present in Table 1.4 reveal that, as the theory outlined above suggests, workers in clusters who separate from their software jobs are more likely to transition to other firms in the same industry directly (i.e., with one quarter or less of intervening non-employment) than they are to move to other industries directly or to take new jobs after a period of non-employment. Holding all other variables constant at their means, separating from a clustered as opposed to an unclustered software establishment boosts the predicted probability of transitioning directly to another software establishment by a significant 4.7%. This result is consistent with poaching by software firms, which would facilitate rapid job-hopping among workers within the industry. Separating from a clustered firm also increases the likelihood of obtaining a new job in a different industry, but by a smaller amount than it promotes direct within-industry transitions.[31] Firms in other industries, though perhaps attaching some value to the skills obtained in software jobs, may not be as actively engaged in poaching software workers as software establishments themselves.

[31] 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 clustering is significant at the 1% level. The results are very similar using a different radius for the LQ and using an establishment-based instead of an employment-based LQ. Including the time-varying LQ (entering either linearly or as a quadratic) instead of including the clustering dummy also yields similar results.

Table 1.4: Worker Destinations following Separations from Software Industry Jobs
Multinomial Logit Model

	(1) Transition Directly to Software	(2) Transition to Software with Intervening Non-Employment	(3) Transition Directly to Different Industry	(4) Transition to Different Industry with Intervening Non-Employment
Clustering Indicator (0/1)	1.6806	1.3405	0.2373	0.1828
	(0.0900)***	(0.0714)***	(0.0384)***	(0.0368)***
	[0.0473]	[0.0093]	[0.0170]	[-0.0024]
Tenure in Current Job (Quarters)	0.0471	0.0255	0.0251	-0.0143
	(0.0086)***	(0.0082)***	(0.0039)***	(0.0037)***
Tenure in Current Job Squared	-0.0015	-0.0007	-0.0012	0.0002
	(0.0004)***	(0.0003)**	(0.0002)***	(0.0001)
Log Annualized Earnings ($1997)	2.2938	1.7525	-0.0750	0.6774
	(0.4166)***	(0.2695)***	(0.0717)	(0.0808)***
Log Annualized Earnings Squared	-0.0926	-0.0697	0.0033	-0.0330
	(0.0185)***	(0.0121)***	(0.0034)	(0.0039)***
Urban Density	1.8070	2.1796	0.1070	-0.6404
	(0.6069)***	(0.4922)***	(0.2592)	(0.2443)***
Log Establishment Employment (FQ)	0.6095	0.5931	0.2811	0.3165
	(0.0501)***	(0.0482)***	(0.0202)***	(0.0194)***
Log Establishment Employment Squared	-0.0603	-0.0552	-0.0292	-0.0370
	(0.0050)***	(0.0049)***	(0.0022)***	(0.0021)***
Constant	-20.1923	-16.2239	-1.6424	-3.7210
	(2.2883)***	(1.4934)***	(0.4067)***	(0.4424)***
Observations (Separations)	130,127			

Controls include worker age, worker age squared, a gender dummy, a race dummy (white/non-white), education dummies (<12 years, 12-15 years, 16+ years), a dummy for prior software industry experience, year and quarter dummies, county dummies, and left censoring dummies (interacted).

Change in predicted probabilities holding other variables constant at means in brackets; change for omitted category -0.0712.

Standard errors in parentheses allow for arbitrary correlation over time within the same person.

* significant at 10%; ** significant at 5%; *** significant at 1%. Based on LEHD data.

The likelihood of transitioning to an establishment in software is increasing in tenure at the separation establishment, earnings at the separation establishment, the size of separation establishment, and whether an individual had software industry experience prior to working at the separation establishment.[32] Greater formal education and lower age, meanwhile, tend to decrease the likelihood of making a job-to-job transition (with or without an intervening spell of non-employment), perhaps because younger and better educated workers are more willing to move out of state when better job opportunities arise.

Having established patterns of job mobility among software workers, I now turn to examining earnings dynamics within the industry.

1.5.2 Earnings Dynamics

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

Empirical Test of Prediction 3: **Workers moving from outside the H industry into a clustered H-type firm will accept earnings discounts relative to workers moving into an isolated H-type firm.**

The model implies that individuals will tolerate 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

[32] Though the model suggests that current earnings, tenure, firm size, and prior industry experience should be positively correlated with establishment productivity in a cluster and hence that the probability of moving from one high-technology firm to another should be decreasing in each (at least on a cross-sectional basis), in a richer model one might expect all these to serve as signals to potential poachers that the worker has accumulated valuable knowledge that she could bring to a new job.

industry. Workers starting in a different industry who take a job at an isolated software 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 fixed effects model that captures workers' earnings histories and identifies the impact of transitioning into a clustered or unclustered software establishment. Adapting the approach of Jacobson et al. (1993) and the program-evaluation literature, I pool information for workers directly transitioning from other industries into their first software jobs at pre-existing firms during the sample period.[33] I then introduce a series of dummy variables for the number of quarters before or after workers' transitions into the industry. In particular, I let $D_{it}^{k} = 1$ if worker i transitions into software from outside the industry in quarter t-k and $D_{it}^{k} = 0$ otherwise. I allow k to range from -12 to 12 and include in the estimation sample only those individuals for whom I have earnings information for the complete six-year window around the time of their transitions into software. Restricting attention to workers with long observed employment histories permits a better use of pre- and post-transition earnings to control for unobserved heterogeneity among workers by mitigating the effect of unusually high or low earnings for individual workers in particular quarters.

To examine the earnings impact of moving from outside software into a clustered as opposed to an isolated software firm, one option would be to interact a dummy for clustering defined for destination software firms with each of the 25 transition dummies; however, inspection of the data reveals that a more parsimonious specification can

[33] I restrict attention to moves into establishments in existence prior to the time at which a worker joins since my goal is to examine the implications of poaching by firms; start-ups and spin-offs essentially represent workers poaching themselves away from their own employers. Inclusion of these workers drives the estimated initial earnings change associated with a job change lower.

capture the relevant effects. Setting a "pre-transition" dummy F_{it}^{1} equal to 1 if worker i transitions into software within three years of time t and 0 otherwise, a "transition" dummy F_{it}^{2} equal to 1 if worker i transitioned into software in the current quarter and 0 otherwise, and three "post-transition" dummies F_{it}^{3} , F_{it}^{4} , F_{it}^{5} equal to 1 if worker i transitioned into software 1-2 quarters ago, 3-8 quarters ago, and 9-12 quarters ago, respectively, and 0 otherwise, I estimate the following model:[34]

$$ln(earnings)_{it} = \alpha + \sum_{m=1}^{5} F_{it}^{m} C_i \beta_m + \sum_{k=-12}^{12} D_{it}^{k} \boldsymbol{M_i \Psi_k} + \sum_{k=-12}^{12} D_{it}^{k} \delta_k + \boldsymbol{\Phi X}_{it} + \eta_t + \varphi_i + \omega_i t + \varepsilon_{it}$$

where $ln(earnings)_{it}$ is the natural log of real annualized earnings of worker i at time t and C_i represents a dummy for firm clustering equal to one if the software establishment into which i transitions has an employment-based LQ greater than or equal to one at the time of transition.[35] $\boldsymbol{M_i}$ is a vector of worker and establishment characteristics at the time of i's move into software that includes log establishment employment, urban density, and dummies for worker gender, race, and education; I include interactions between the elements of $\boldsymbol{M_i}$ and each of the 25 dummy variables D_{it}^{k}, $k = -12, -11, \ldots, 11, 12$, in order to isolate the earnings consequences of transitioning into a clustered or unclustered firm holding constant the distributions of these time-invariant characteristics across movers. $\boldsymbol{X}_{it}$ in the regression represents a vector of time-varying person characteristics at t that includes a quadratic in age, and η_t is a time dummy.

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[34] Since I observe some workers for longer than three years on either side of their time of transition into software, all the parameters of the model are identified.

[35] The results are robust to using the time-varying LQ (entering linearly or as a quadratic) instead of the clustering dummy, as well as to using clustering dummies defined using radii fewer than 25 miles and using the average LQ over the spell.

Critically, the person fixed effect, $\alpha + \varphi_i$, captures worker heterogeneity in observed and unobserved characteristics that do not vary over time, thereby mitigating biases that might arise if transitions into software and their earnings consequences occur at least in part because of enduring individual characteristics.[36] I also include a worker-specific time trend, $\omega_i t$, to account for possible differences across workers in trend rates of earnings growth. Since the observations for each person are likely not independent over time, I correct standard errors by clustering on worker; that is, the error term ε_{it} is assumed independent across workers but not necessarily within workers over time.

Table 1.5 reports results for the fixed effects model.[37] Holding constant the distribution of other worker and firm characteristics at the time of transition, there is little discernable difference in pre-transition earnings dynamics among workers who ultimately enter clustered software firms as opposed to unclustered firms. However, at the time of transition, workers who obtain jobs at clustered establishments accept significantly lower starting earnings relative to workers who take jobs at unclustered firms. The immediate earnings discount for those entering clustered as opposed to unclustered firms amounts to roughly 5%.[38] Earnings growth among those starting at clustered firms remains depressed compared to growth among those at unclustered establishments for up to two years before showing signs of a relative recovery, though the effects beyond the initial impact in the quarter of transition are insignificant.

[36] The worker fixed effects subsume the independent effects of each of the variables in $\boldsymbol{M_i}$, which are all defined as of the time of transition for each individual in the estimation sample.
[37] An F test for the null hypothesis that $\varphi_i = 0$ for $i = 1, 2, \ldots$ leads to rejection at the 1% level.
[38] One can calculate the percentage effect on earnings from the coefficient estimates as $e^{\beta} - 1$.

Table 1.5: Earnings Consequences of Job Transitions into the Software Industry

Fixed Effect Model (Worker Fixed Effects)	
Transition into Clustered Software Establishment x	
Pre-Transition Period (1-12 Quarters before Move)	0.0088
	-0.0189
Transition Period (Quarter of Move)	-0.053
	(0.0231)**
Post-Transition Period (1-2 Quarters after Move)	-0.0105
	-0.0193
Post-Transition Period (3-7 Quarters after Move)	-0.0085
	-0.019
Post-Transition Period (8-12 Quarters after Move)	0.0177
	-0.0195
Transition Period Dummy D_{it}^{0} (Quarter of Move)	0.0818
	-0.0823
Age (Years)	0.2514
	(0.0173)***
Age Squared	-0.0021
	(0.0001)***
Constant	4.8345
	(0.5000)***
Observations (Job x Quarter)	97,759

Controls include worker fixed effects; 24 pre- and post-transition quarter dummies (D_{it}^{k}, k = -12, …, -1, 1, …, 12); complete set of interactions of 25 transition quarter dummies (D_{it}^{k}, k = -12, …, -1, 0, 1, …, 12) with software establishment size, urban density, and dummies for worker gender, race, and education; worker-specific time trends, and year and quarter dummies.
Standard errors in parentheses allow for arbitrary correlation over time within the same person.
* significant at 10%; ** significant at 5%; *** significant at 1%.
Based on LEHD data.

The results in this section suggest that, relative to those who obtain jobs at unclustered firms, workers who take jobs at clustered establishments experience significantly lower initial earnings and perhaps at least a short period of relatively weak wage growth. Yet these exercises include only individuals moving into software from jobs held outside the industry and are limited in the extent to which they control for variation in software establishment characteristics. In estimating clustering's effect on earnings-tenure profiles in the next section, I broaden the sample to include all software job spells and take further steps to account for underlying worker and firm heterogeneity.

Empirical Test of Prediction 4: **Workers inside a cluster will experience faster earnings growth and face steeper earnings-tenure profiles than workers outside a cluster.**

Individuals in the model enjoy relatively steep wage-tenure profiles in high-technology industry clusters as firms compete over skilled labor. In this section, I estimate a panel regression that controls for both observable and unobservable worker and firm characteristics in order to isolate the true effect of clustering among software establishments on earnings patterns. I model heterogeneity across workers and establishments explicitly by assuming that each job has its own specific earnings intercept, $\alpha + \theta_{ij}$. This fixed effect model, which eliminates both unobserved worker-level and establishment-level time-invariant error components, is specified as follows:

$$ln(earnings)_{ijt} = \alpha + \beta_1 tenure_{ijt} + \beta_2 tenure_{ijt}^2 + \beta_3(C_{ij}*tenure_{ijt}) + \beta_4(C_{ij}*tenure_{ijt}^2) + \beta_5 U_{ijt} + \beta_6(U_{ijt}*tenure_{ijt}) + \beta_7(U_{ijt}*tenure_{ijt}^2) + \boldsymbol{\Phi X_{it}} + \boldsymbol{\Omega Z_{jt}} + \theta_{ij} + \eta_t + \varepsilon_{ijt}$$

where $ln(earnings)_{ijt}$ is the natural log of real annualized earnings of worker i at establishment j at time t, $tenure_{ijt}$ is accumulated tenure for i at j as of t, C_{ij} represents a dummy for firm clustering equal to one if establishment j has an employment-weighted LQ greater than or equal to one in the majority of the quarters over which the spell ij is observed, U_{ijt} is the urban density variable, $\boldsymbol{X_{it}}$ represents a vector of time-varying person characteristics at t that includes age and age squared, $\boldsymbol{Z}_{jt}$ represents a vector of time-varying establishment characteristics at t that includes a quadratic in log employment, and η_t is a time dummy.[39] I interact the clustering dummy with tenure to shed light on how agglomeration affects the shape of the earnings-tenure profile.[40] I also include interactions between tenure and urban density to determine the extent to which being located in an economic dense area independently affects wage growth and to ensure β_3 and β_4 capture only the marginal impact of clustering among software establishments on workers' earnings-tenure profiles. 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.

An attractive feature of the fixed effect approach in this section, much as in the prior section, is that it helps to mitigate any bias that might arise because workers self-select into clustered establishments. If more innately talented individuals select into clustered establishments, estimates of the earnings effects of clustering would be biased upward. Using job fixed effects, which are defined for each unique worker-establishment match, also mitigates potential problems stemming from firms' endogenous location decisions; whether a firm decides to cluster depends on its assessment of the benefits and costs associated with labor pooling and poaching. To the extent that unobservable but time invariant factors affect firms' location decisions, job fixed effects will resolve the endogeneity problem associated with firm location choice. Meanwhile, including time

[39] The results are robust to using the establishment-specific time-varying LQ instead of the clustering dummy variable (with or without a quadratic in the LQ), as well as to using clustering dummy variables defined using radii fewer than 25 miles and using the average LQ over the spell.
[40] The clustering dummy variable itself is subsumed in the fixed job effect.

dummies eliminates bias due to any correlation between clustering and earnings resulting from shocks that vary over time but that are constant across jobs.

While the fixed effect approach permits the error terms to be correlated with the job effects, the inclusion of job fixed effects drastically diminishes the number of degrees of freedom in the regression and precludes one from obtaining parameter estimates for time-invariant job, worker, and establishment characteristics. In the fixed effect framework, time-invariant characteristics, including the job-specific clustering dummy variable, are subsumed by the unit-specific intercepts, which are assumed to be non-stochastic. Nonetheless, it provides a way to address several sources of bias in estimating clustering's effect on the shape of the earnings-tenure profile.[41]

The results of the fixed effects regression appear in Table 1.6.[42] Earnings are increasing at a diminishing rate in tenure, as expected. Furthermore, the interaction terms suggest that workers employed at clustered establishments reap relatively large returns to

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[41] Random effects models permit one to obtain coefficient estimates for time-invariant worker and establishment characteristics and are not subject to the degrees-of-freedom problems to which fixed effects models are prone. Therefore, as a check and extension on my preferred fixed effects approach, I estimate a random effects 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 random effects specification is

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

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}. I add to the vectors $\boldsymbol{X}_{it}$ and $\boldsymbol{Z}_{jt}$ time-invariant worker and establishment characteristics including dummies for worker gender, worker race, worker education, establishment clustering, and establishment county. All other variables are defined as before, and left-censoring dummies are incorporated in the random effects model where required. The results of the random effects model are qualitatively similar to those of the fixed effects model.

While the random effects approach holds some advantages over the fixed effects 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 random effects model would yield inconsistent parameter estimates. A Hausman test for fixed effects versus random effects models generates a Chi-squared statistic that implies that I can reject the null hypothesis that the coefficients in the two models are identical. This suggests that, given that the model is correctly specified, the coefficients from the random effects model may not be consistent.

[42] An F test for the null hypothesis that $\theta_{ij} = 0$ for $ij = 1, 2, \ldots$ in the model leads to rejection at the 1% level.

tenure controlling for other worker and firm characteristics, both observable and unobservable. This is consistent with the model outlined above, in which workers in clusters face steeper earnings-tenure profiles as a result of the strategic interaction of firms as they compete over skilled labor. 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).

Table 1.6: Earnings-Tenure Profiles in Software Industry Jobs
Fixed Effect Model (Job Fixed Effects)

Observed Tenure (Quarters)	0.0100
	(0.0011)***
Observed Tenure Squared	-0.0002
	(0.0000)***
Clustering Indicator x Tenure	0.0014
	(0.0004)***
Clustering Indicator x Tenure Squared	0.0000
	(0.0000)
Urban Density	2.5552
	(0.1822)***
Log Establishment Employment (FQ)	0.0733
	(0.0067)***
Log Establishment Employment Squared	0.0014
	(0.0007)**
Age (Years)	0.1230
	(0.0047)***
Age Squared	-0.0012
	(0.0000)***
Constant	7.4453
	(0.1508)***
Observations (Job x Quarter)	1,522,806

Controls include job fixed effects and year and quarter dummies.

Standard errors in parentheses allow for arbitrary correlation over time within the same job.
* significant at 10%; ** significant at 5%; *** significant at 1%.
Based on LEHD data.

Importantly, job fixed effects absorb the impacts of time invariant but unobservable worker and firm characteristics whose omission from the regression might otherwise cloud estimates of clustering's effect on earnings patterns. As previously discussed, 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 dynamics. After addressing these sources of bias and controlling for observed and unobserved worker and firm heterogeneity, what is left is the key result that establishment clustering in the software industry interacts positively with worker tenure. The finding that earnings-tenure profiles are steeper in clusters is consistent with the idea that agglomeration fosters competition over workers that affects software firms' compensation strategies.

1.6 Conclusion

This chapter 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 software publishing 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 isolated software establishments, controlling for worker and establishment heterogeneity.

By shedding light on the complex ways in which geography can interact with labor markets to affect individual worker outcomes, this work makes contributions to the macro, labor, and urban and regional economics literatures. It also opens up numerous avenues for future research. While I concentrate in this chapter on the predictions of my model for worker job mobility and earnings dynamics, the model also has implications for the location decisions of firms, suggesting further theoretical and empirical exploration of how firm and industry characteristics could influence the spatial distribution of economic activity.

With respect to the empirical analysis in this chapter, a more careful treatment of endogeneity issues in the job mobility and earnings regressions may be warranted. This work makes some progress toward mitigating biases resulting from the simultaneity problem that arises due to worker self-selection into clusters, but different empirical approaches (such as an instrumental variable approach) could, at the very least, serve to substantiate the results. Examining other industries could also help to corroborate my empirical work as well as elucidate the precise nature of the benefits and costs that firms face when clustering. For sectors in which industry-specific skills are less important, such as 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. This might provide an incentive for businesses in some industries to disperse that, in concert with other drivers of employer location decisions, would affect the geographic distribution of firms and thereby impinge on local labor market dynamics.

Chapter 2

Reaching for the Stars: Who Pays for Talent in Innovative Industries?[*]

2.1 Introduction

The process of innovation is wrought with both promise and risk, requiring substantial investments of time and money with uncertain payoffs. Identifying how, in the face of such uncertainty, firms recruit and motivate talented individuals and workers ultimately sort themselves across firms is critical to understanding the innovation process as well as observed changes over time in the structure of earnings in the U.S. economy. This chapter draws key connections between employers' hiring practices and product market risk in the realm of high technology. We show that software firms that operate in product markets with highly skewed returns to innovation pay a premium to hire highly talented workers. These same firms reward loyalty; that is, talented workers who stay with their employers enjoy much higher earnings in firms that face greater variance in the potential payoffs from innovation.

The software industry is often viewed as the poster-child for the advanced technology sector, and segments of the industry can be very risky indeed. Video games are at or near the top of the list for high stakes product development; some games generate huge returns for their creators, while others languish on store shelves. That said, in the same industry, some product lines present firms with substantially less risk. For instance, in the case of business applications software, once a sufficiently large

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[*] This chapter draws on a joint paper with Fredrik Andersson, John Haltiwanger, Julia Lane, and Kathryn Shaw with the same title. The authors thank Tim Bresnahan, Charlie Brown, Ben Campbell, Erica Groshen, Phil Hardiman, Edward Lazear, Alex Mas, Paul Oyer, and Julie Wulf as well as seminar participants at Stanford University, Washington State University, the University of California-Santa Barbara, and the Society of Labor Economists meetings for their helpful comments.

community has adopted an application, software producers have an installed client base that provides a degree of stability for future product development. This chapter exploits this within industry variation in potential payoffs across product markets to explore how such variation maps into firms' different approaches to attracting, motivating, and retaining talented workers.

To investigate the link between the differential payoff distribution for different types of products and the hiring and compensation policies of firms in the software industry, we use a rich new longitudinal employer-employee matched data source that permits us to track both firms and workers over time. On the firm side, we have rich information about the detailed product mix and revenue outcomes of each business, which permits us to measure both its potential payoffs and its actual performance. On the worker side, we can measure earnings levels (including the contribution of exercised stock options and bonuses) as well as within-job and between-job earnings growth.

The theoretical motivation for the empirical analysis begins with the assumption that innovative firms want workers who are good at designing or selecting new projects. The key insight of our model is that some firms value this talent more than other firms (Lazear 2005). In a product market in which innovation is rarely rewarded, or in which even a great project will generate small returns, the payoff distribution has a relatively low variance and firms in the market attach less value to worker talent. On the other hand, in a product market in which the payoff distribution has a greater variance, as it does in the video game example above, firms attach greater value to individual talent, since those that pick projects well can reap relatively large returns. Based on these ideas, our model predicts that firms that operate in product markets with greater variance in potential payoffs will hire more talent and pay higher wages.

Using our unique micro-data, we first show that, consistent with the model, firms that face greater risk in the product market, and that consequently wish to attract more talent, pay more in starting salaries than other firms. These firms select talented workers who themselves have a history of prior success (i.e., they hire workers who have in the past had high wage levels). Second, we show that firms in riskier product lines reward workers more for loyalty; that is, we find that those software workers who achieve the highest earnings do so by remaining at firms in product markets characterized by greater variance in payoffs.

In short, our analysis reveals that firms that operate in more dynamic, risky product markets select the most talented workers and pay them both higher starting salaries and higher performance pay. These innovating firms offer skilled individuals substantial sums of money up front because they are betting on a high-stakes game of producing winning high-payoff products. They also pay for stars with performance pay aimed at rewarding loyalty, which further increases the likelihood of success in the marketplace.

This work represents an advance on empirical and theoretical fronts. Previous empirical work seeking to establish a link between product markets and compensation policy has focused almost entirely on CEO pay and has, by and large, identified CEO compensation as a function of firm size or underlying strategies. The few "insider" studies that exist find evidence of a connection between strategy and pay within individual firms that stretches across their workforces to varying degrees (Baker and

Hubbard 2003; Stern 2004; Wulf 2002, 2005; Garicano and Hubbard 2005). Studies that employ survey data to examine the subject derive similar results (MacLeod and Parent 1999). Each of these strands of the literature, though, suffers from a narrow focus, inaccurate or incomplete data, or both. From an empirical standpoint, by using a rich employee-employer matched data set, this work vastly expands our understanding of the nature and scope of the connection between product markets and compensation policy.

This work also closes some of the gap between the theoretical and empirical models of incentive contracts and sorting. As the information industry has become an increasingly dominant part of the U.S. economy, research specifically on workers in high-technology sectors has blossomed (Chevalier and Ellison 1999, Garicano and Hubbard 2005, Fallick et al. 2006, Lerner and Wulf 2005). However, while theoretical models of incentive pay may state the conditions under which firms optimally adopt different forms of pay, empirical researchers have, at best, showed that some firms succeed and others fail with a given compensation policy. Efforts to document the adoption of different compensation schemes empirically have been stymied by data limitations. In this study, we show that incentive pay plans and sorting based on talent are optimal in firms with high potential payoffs in their respective product markets, and we find evidence consistent with these phenomena.

On a broader level, the human resource practices of firms operating in innovative markets help to shape patterns of earnings inequality in the economy. Talent at such firms is valuable, and the relationships that we identify between product market strategies and compensation policy in innovative markets help to explain not only increases in the variance of starting salaries across workers, but also the widening of pay differentials over time. Indeed, our findings shed light on relevant factors affecting the polarization of earnings at the upper end of the earnings distribution (Autor et al. 2006). The results suggest that in high-technology industries such as software, where potential payoffs vary across product markets, a driving force behind the growing earnings gap between workers at the top and everyone else are firms' efforts to adapt their human resource practices to their particular business environments.

The chapter proceeds as follows. In the next section, we provide some background facts about the software industry to help motivate our analysis. We outline our application of Lazear's (2005) model linking product market risk and pay policy in Section 2.3, and we provide a detailed description of the data we use to test the predictions of the model in Section 2.4. In Sections 2.5 and 2.6, we present our empirical specifications and the results from these specifications. We conclude and discuss the implications of our work in Section 2.7.

2.2 Background

In this section, we present a set of basic facts aimed at describing the wage distribution of workers and the potential payoff distribution facing firms in different product markets in the software industry. These facts will help to motivate the approach and analysis that follows.

First, not only do workers in the software industry have relatively high salaries on average, but a small subset of workers in the industry receive extraordinarily high wages. Panel (a) of Table 2.1 provides summary statistics about the distribution of income from the 2000 Decennial Census Public-Use Microdata Sample (PUMS) for workers in all industries as well as for workers specifically in the software industry.[43]

[43] We focus on full-time workers between 21 and 44 years of age. For the purposes of our analysis, we define the software industry as SIC 7372 (prepackaged software).

Table 2.1: Summary Earnings Statistics
Workers 21-44

	Mean	Median*	90th*	SD
(a) 2000 Decennial Census (PUMS) Data - 35+ Hours/Week & 35+ Weeks/Year				
All Industries				
Total Earnings	40,918	31,891	70,160	183,134
Wage and Salary Income	38,685	31,466	69,097	173,449
Software Industry (SIC 7372)				
Total Earnings	80,787	63,782	127,563	334,906
Wage and Salary Income	80,006	63,782	127,563	333,669
Computer Software Engineers (Census Occupation Code 102) in the Software Industry				
Total Earnings	90,668	70,691	138,193	369,374
Wage and Salary Income	90,496	70,160	138,193	369,777
(b) LEHD Data for Ten States - Earning $50,000+ Annualized				
Software Industry				
Starting Earnings (Excludes Left-Censored)	69,353	59,665	108,692	82,432
Ending Earnings (Censored and Uncensored)	344,268	95,508	310,644	2,051,985
One-Year Prior Earnings (Censored and Uncensored)**	199,172	86,796	220,760	1,101,658
Prior-Spell Ending Earnings***	60,951	51,532	100,987	133,153
Top Decile of Workers (by Ending Earnings) in Software Industry				
Starting Earnings (Excludes Left-Censored)	107,660	80,899	184,951	142,526
Ending Earnings (Censored and Uncensored)	2,532,500	670,993	6,688,470	6,064,204
One-Year Prior Earnings (Censored and Uncensored)**	750,551	171,642	1,338,380	2,862,843
Prior-Spell Ending Earnings***	98,467	73,434	164,194	150,428

* Average within a 10% band around the true percentile. ** Annualized earnings three quarters prior to last observed full quarter.

*** Includes only individuals for whom we observe a prior spell in the data.

As panel (a) reveals, based on either mean or median figures, workers in the software industry as a whole earn more than twice what workers in all other industries earn. The PUMS data further suggest that, while the variance of pay in software is relatively large, compensation is not appreciably more skewed to the right for workers in software than in other industries. However, the figures in panel (a) do not capture performance bonuses and stock options, possibly important means of compensation in software. Further, with PUMS information alone, we cannot distinguish recent hires from experienced workers, which limits our ability to examine starting salaries and earnings-tenure profiles in the industry.

To address these deficiencies, we present summary statistics in panel (b) of Table 2.1 derived from data from the Longitudinal Employer-Household Dynamics (LEHD) Program at the U.S. Census Bureau. These data are built from employer-filed unemployment insurance (UI) records, which contain data on all earnings, including bonuses and stock options.[44] Because UI data do not contain hours of work or occupation information, we restrict our sample to workers earning at least $50,000 on an annual basis in the software industry.[45] Moreover, we focus on job spells in the software industry that are ongoing in 1997, as this sample of spells is useful for our later analysis exploiting firm level characteristics.

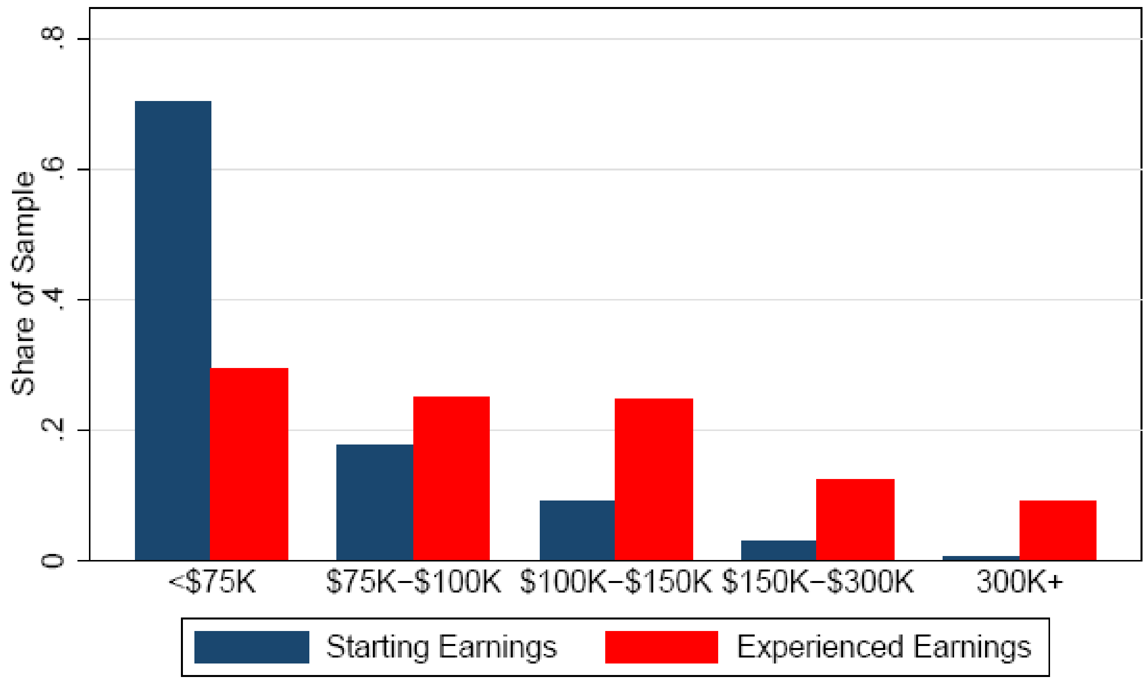
[44] These data are described in greater detail in our data section.

[45] The $50,000 threshold is discussed in more detail below, but it is worth noting that in the PUMS data, two-thirds of all software workers and four-fifths of software engineers have total earnings of at least $50,000. Indeed, the mean of total earnings for software engineers in SIC 7372 earning at least $50,000 is $103,881, only slightly higher than the $90,668 reported in Table 2.1 for workers at all earnings levels. It is also worth noting that the $50,000 represents the worker's earnings when we last observed him or her in the data; 36% of those earning $50,000 or more when we last observe them have starting salaries less than $50,000. Fortunately, Table 2.1 (as well our robustness analysis discussed in more detail below) indicates that by using a relatively simple income cutoff, we can identify the software developers and managers in the administrative data. That is, focusing on workers earning more than $50,000 annually in constant 2001 dollars yields workers that are well identified as software developers and managers.

The longitudinal nature of the data permits us to construct numerous different measures of earnings for software workers, and we report in panel (b) earnings for new hires (measured as annualized earnings at the start of the observed job spell excluding left-censored records), earnings for experienced workers (measured as annualized earnings at the end of the observed spell), earnings of workers one year prior to the end of the observed spell (or starting earnings if the spell was less than one year long), and earnings of workers in the last quarter of their prior spells (conditional on our observing the prior spell). There are left and right censoring issues that we address in the standard ways in our econometric analysis below, but even with these limitations, we see a number of interesting patterns in panel (b) of Table 2.1. Not only are ending earnings much higher than starting earnings, but they are also very skewed to the right. The skewness is especially pronounced for the most highly paid workers (the top decile in terms of ending earnings). The median exceeds \$670,000 and the 90th percentile nearly \$6.7 million for ending earnings, compared with a median of only about \$81,000 and a 90th percentile of \$184,000 for starting earnings. This suggests that a select group of workers have enormous average within spell wage growth at both the median and especially at the 90th percentile. At least a fraction of the high ending earnings could be bonuses or exercised options upon leaving the firm, which makes examining earnings patterns one year prior to the end of spell also potentially relevant.

Another key characteristic regarding the nature of compensation in the software industry is that the pay of software workers rises markedly with tenure. Figure 2.1 compares the earnings distribution of salaries for new hires (excluding left censored spells) to the distribution for experienced workers (ending earnings if the spell is not censored and the last observed earnings otherwise). While 70% of starting earnings are below $75,000, only 29% of experienced workers earn below $75,000 (experienced workers have an average tenure of five years). Similarly, only 4% of starting salaries are above $150,000, but 21% of experienced workers earn above that amount. Since starting salaries include the salaries paid to new but experienced workers, earnings rise markedly with tenure.

Figure 2.1: Distribution of Starting Earnings and Experienced Earnings
SIC 7372, Experienced Workers 21-44 Earning $50,000+



Starting earnings excludes left-censored job spells.
Based on LEHD data for ten states.

A final pertinent feature of the software industry is that there appears to be a high variance to the gains to innovation in a number of product lines. As an illustrative example, we present in Table 2.2 the distribution of revenues for the top ten video games in 2002. The distribution is highly skewed, even restricting attention to the top ten games. Indeed, the top game earned nearly five times as much as the tenth on the list.

Table 2.2: Top Video Games in 2002 Ranked by Sales Revenues

Game	Firm	2002 Revenues (Millions)
Grand Theft Auto Vice City	Take 2	$218
Grand Theft Auto 3	Take 2	$120
Madden NFL 2003	Electronic Arts	$119
Medal of Honor	Electronic Arts	$73
Kingdom Hearts	Square Enix	$59
Spider Man	Activision	$54
Halo	Microsoft	$51
SOCOM Seals	Sony	$50
Super Mario Sunshine	Nintendo	$49
Tony Hawk	Activision	$46

Based on Merrill Lynch's “Reinstating Coverage of Video Game Industry” report (January 21, 2004).

As mentioned in the introduction, though, not all software firms face such a skewed payoff distribution for their products. In the consumer video game market, the costs of consumers switching to a new game is minimal, and hence firms in the market have enormous potential gains if the product does succeed in the market. However, the same is not true for firms that produce, for instance, enterprise resource software for large mainframe computers. Such firms tend to have lower variance payoffs, as customers are often locked into a software product and purchase it (or merely upgrades) on an ongoing basis. The provider in this case is profitable, but software product innovations do not have enormous upside potential gains. An example of this is the SAS Institute, which produces statistical software for businesses. SAS sells its software to firms through licenses, which have about a 97% renewal rate (Pfeffer 1998).

Our empirical analysis encompasses software firms operating in product markets that span the spectrum from having high variance in potential payoffs, as in video games, to having low variance in potential payoffs, as in enterprise software. Before turning to our results, though, we outline in what follows a model that links the skewness of firms’ potential payoff distributions to their hiring and compensation policies, and in particular to their propensity to reward talent and loyalty.

2.3 Model of Innovation

We model the process of producing innovative software products, though this process may well apply to innovations undertaken by most knowledge workers. The fundamental characteristic of software production is the uncertainty that arises because of firms' inability to predict whether an innovative product will pay off.[46] In software innovation, there are two integral groups of employees, each of which faces a degree of uncertainty and risk. On the one hand, programmers and engineers must begin working on a new software project not knowing whether they will develop a great product. On the other hand, managers must allocate funds to research projects not knowing whether the resulting products will succeed in the market. Thus, a model of project selection pertains to the work of programmers and engineers as well as managers.

Given the uncertainty about the likelihood of success for a given project, the key role of an employee seeking to make innovations is to create or pick the best projects. A model by Lazear (2005) demonstrates how employees who are skilled at creating or picking projects should be sorted among firms operating in high variance payoff markets. Assume that projects can have two outcomes, a good outcome that occurs with probability P, and a bad outcome that occurs with probability $(1-P)$. Uncertainty derives from the fact that ex-ante, software programmers and managers cannot identify which projects are good and which are bad. As a result, they can make false positive errors,

[46] There are other related forms of uncertainty about product market payoffs that fit within the framework of our model. Suppose, for example, that a component of the uncertainty relates to whether workers implement a new idea effectively. In this case, the talented programmers may be those that implement the idea well (e.g., without problematic bugs or other product market features that would have an adverse impact on the returns from the product).

denoted H', by accepting projects that they believe are good but that later turn out to be bad as well as false negative errors, denoted $1\text{-}H$, in which they reject a project that would have turned out to be a good project. More specifically, a false positive is defined as

$$H' \equiv Pr(\text{accept a project} \mid \text{project is actually bad})$$

A false negative, on the other hand, is defined as

$$1 - H \equiv 1 - Pr(\text{accept a project} \mid \text{project is actually good})$$

Assume that if a firm chooses to undertake a good project and it pays off, the firm earns $\$X$. If, on the other hand, a firm chooses to undertake a project that turns out to be bad, it costs the firm $\$Y$. A firm has zero costs and zero revenue if it rejects projects early. Given these probabilities and net revenues, the expected payoff for a firm is

$$E(payoff) = PHX - (1\text{-}P)H'Y + P(1\text{-}H)*0 + (1\text{-}P)(1\text{-}H')*0$$

which simplifies to

$$E(payoff) = PHX - (1\text{-}P)H'Y$$

Firms that achieve a high payoff are those that have a high value of *PHX*. Firms that fail, meanwhile, are those that have a high value of the losses, $(1-P)H'Y$.

Lazear (2005) defines a "star" worker as an individual who has a higher probability of accepting truly good projects and a lower probability of accepting truly bad projects. This ability could stem from innate talent, be developed as human capital on the job through learning, or arise from higher effort in response to incentives. In any event, star programmers must develop great projects and star managers must allocate resources to them. Both sets of skills are important determinants of success in the software industry. Thus, we define

$$H + \varepsilon \equiv \textit{Star's Pr(accept or develop a project} \mid \textit{project is actually good)}$$

and

$$H' - \varepsilon \equiv \textit{Star's Pr(accept or develop a project} \mid \textit{project is actually bad)}$$

where ε captures the quality of the star worker, or the talent that person has in picking projects relative to non-star workers. Therefore, the value of selecting a star employee relative to a non-star employee, Δ, is the incremental expected payoff,

$$\Delta = [P(H + \varepsilon)X - (1 - P)(H' - \varepsilon)Y] - [PHX - (1 - P)H'Y]$$

or, more simply,

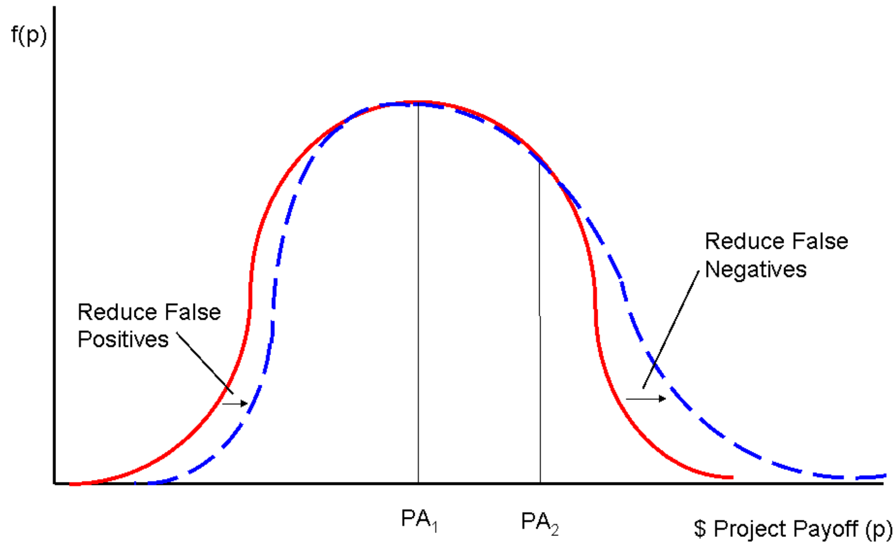
$$\Delta = \varepsilon[PX - (1 - P)Y]$$

Hence, firms in high variance payoff markets value star talent the most, since firms that have either high potential payoffs from good project selection (large $\$X$) or large potential losses from bad project selection (large $\$Y$) gain the most from having stars with extra talent ε.

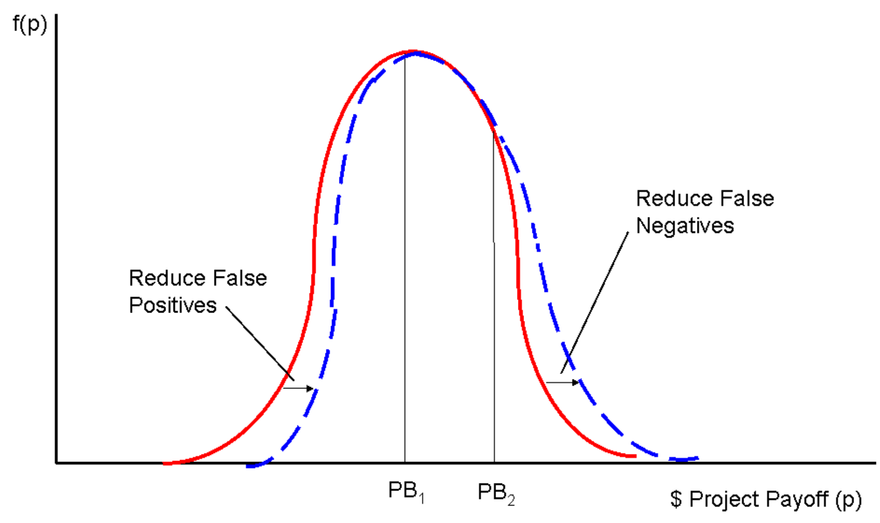
We illustrate this implication with a continuous distribution of payoffs in Figure 2.2. The continuous distribution of payoffs is consistent with the model above in that, while a firm might have a range of possible projects with different potential payoffs, any given project might have the types of payoffs and probabilities previously described.

Figure 2.2: Shifts in the Payoff Distribution Due to Reductions in False Positive or False Negative Errors

(a) More Risky Payoff Distribution



(b) Less Risky Payoff Distribution



The bold line in Figure 2.2(a) shows a high variance payoff distribution, while the bold line in Figure 2.2(b) shows a low-variance payoff distribution. The dotted lines in (a) and (b) are the changes in the distributions attributable to star talent. In each case, the left tail shifts right due to stars because employing such workers reduces the occurrence of false positives; that is, for any given project, a star reduces by ε the probability H' of accepting a project that is bad and, as a result, losing $(1-P)Y$. The right tail shifts right because stars also reduce the number of false negatives; that is, for any given project, a star increases by ε the probability H of accepting a project that is good and has payoff PX.

Thus, by shifting the payoff distribution to the right, the mean payoff rises from PA_1 to PA_2 in the payoff distribution of Figure 2.2(a). This is the gain associated with paying for a star worker, a gain that must exceed the cost of hiring that employee. Figure 2.2(b) depicts a narrower underlying project payoff distribution, which would arise when projects are less risky and thus potential losses as well as gains are smaller. When a star shifts this low-risk payoff distribution due to their talent for project assessment, the mean gains are smaller; in that case, the gains are $PB_2 - PB_1$. As is evident in the figures, the gains to stars are smaller in low-risk product markets than in high-risk product markets, as $(PB_2 - PB_1) < (PA_2 - PA_1)$. In sum, because there are larger gains (or smaller losses) to the selection of great projects in high-risk product markets, stars are more valuable in (a), where potential payoffs are higher, than in (b), where potential payoffs are lower.

Primary Hypothesis: **Firms operating in product markets that have high variance payoffs should pay higher wages, because these firms hire and reward more highly talented software workers.**

Underlying this hypothesis is the idea that firms in high variance product markets have human resource practices aimed at selecting, developing, and rewarding highly skilled workers. We cannot directly observe firms' human resource practices, but we do observe in our data all the wages within each software firm, which in turn reflect these practices. Our empirical analysis revolves around exploring the relationship between the variance of product market payoffs across different software firms and various dimensions of the wage structure.

Left open is the question of what mechanisms firms with high variance product markets use to attract and retain stars. For example, firms could devote a lot of resources to selecting star workers carefully, or alternatively they could allocate more resources to training workers on the job and providing strong incentives that reward (and sort) star workers over time as they gain experience within the firm.[47] The simple model above is silent about whether such firms will reward star workers though high initial wages or through sharply rising wage-tenure profiles (potentially via bonuses or stock options). However, our data permit us to make these distinctions, and we examine in our empirical analysis the specific nature and structure of the compensation schemes that firms adopt.

2.4 Data

In order to study the connection between the structure of firms' product market strategies and skill demand, we require a dataset with detailed information on the earnings and employment histories of workers as well as on the product market characteristics of the firms at which these workers are employed. We take advantage of a

[47] Additional ways that firms can reward star performers is by assigning them to the most desirable projects or by furnishing them with time to do their own publishable work. Stern (2004) shows that star scientists "pay" to be in more R&D intensive firms by accepting lower wages early in their careers.

unique employer-employee matched data set constructed and maintained by the U.S. Census Bureau's LEHD Program. We further augment the LEHD data with highly detailed firm characteristics from the Economic Census and worker characteristics from the 2000 Decennial Census PUMS.

2.4.1 The Software Industry

We test the hypotheses of our model by focusing on the prepackaged software industry, which corresponds to the four-digit SIC 7372.[48] This narrow focus has a number of key advantages. The first is the payoff structure across different product categories within the sector. In many software product lines, the payoff distribution is characterized by high variance, which the video game example in Table 2.2 vividly illustrates. As we show below in our results, in such product markets, there are substantial rewards to producing successful products.

The second advantage of our focus on SIC 7372 is the close link between the firm and the product in the industry. Software firms in many product markets tend to be R&D intensive units with high variance payoffs to innovation. By contrast, many traditional industries, such as automobile manufacturing, while characterized by R&D intensive segments, are not innovative across the board. An additional related advantage of studying the software industry is the ability to trace directly the performance of its primary employees, including software developers and managers, and to link employee performance to the payoff structure of the firm. In other industries, the "knowledge"

[48] The Census defines SIC 7372 as "establishments primarily engaged in designing and developing prepackaged software, including operating, utility, and applications programs. These establishments may also prepare software documentation for the user, install software for the user, and train the user in the use of the software. Establishments primarily engaged in buying and selling prepackaged software are classified in Wholesale or Retail Trade. Custom computer software services, including computer code authors, are classified in Industry 7371." In the conversion to the new industry classification scheme, SIC 7372 was split into NAICS 51121 (Software Publishing) and NAICS 334611 (Software Reproducing).

workers are a smaller component of total employment and have a less direct impact on the output of their employers.

A final advantage of studying software is the richness of the available data. In the Economic Census surveys it conducts every five years, the U.S. Census Bureau collects a broad array of information on firms that produce software. The data that the Census Bureau collects for the software industry include detailed product line information (described below), which we in turn use to construct a measure capturing the variation in the payoff structure by product. The Economic Census data also provide information on the size and age of firms, which may serve as important controls to the extent that these characteristics are correlated with product market strategies in the software industry.[49]

2.4.2 The LEHD Data

We derive data on software workers from a larger database created by the LEHD Program housed at the Census Bureau. The LEHD Program's longitudinal wage database is based on the quarterly records of the employment and earnings of individuals from UI data, which is in turn matched to internal administrative records and surveys containing information on workers' date of birth, race, and sex.[50]

These data have several important advantages. First, since the scope of the LEHD data is nearly the full universe of employers and workers, we can accurately track the

[49] We thank Ron Jarmin for sharing information on firm age with the LEHD Program for this project.

[50] 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 a unique "Protected Identification Key." 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 5 years in jail.

movements of workers through the earnings distribution within firms as well as across firms over time.[51] Second, in contrast to survey-based information, the earnings data represent the earnings that firms actually pay workers as opposed to workers' memories of their earnings.

A third key benefit of using these administrative data, particularly in the context of this study and the time frame we consider, is that the earnings measures include bonuses and exercised stock options (though not fringe benefits).[52] Obviously, valuing stock options is quite difficult; in this case, the options are valued when they are exercised, or when the employee cashes in the options. We do not have data on when options are granted to employees. However, our sense is that the exercised options available in our data are the preferred measure of pay for our analysis, rather than options granted to employees. Indeed, as Oyer and Schaefer (2002) point out, it generally takes about four years for stock options to be fully vested. Further, as Russell (2005) notes, for a typical software company, options are worth nothing for an employee's first two years, and then are vested at a rate of 2% per month for the remaining three years. Thus, the value of options that a given firm grants depends not only on whether an employee stays with the firm until the options are vested, but also on the growth of the stock price of the company.

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[51] There are important exceptions. Most federal employment as well as some agricultural and nonprofit employment is not covered. Independent contractors and self-employed individuals are also not covered. See Stevens (2002) for a full discussion of coverage issues.

[52] To our knowledge, no previous studies have included stock options data for such a wide range of workers across firms. The nature of our data permit us to exploit the fact that in most employment contracts, employees must exercise all options within 90 days of leaving the firm. We are able to track the earnings of employees for those 90 days and we can thus capture the value of all exercised options. For the laws surrounding the reporting of options, see the example from the California Employment Development Department at http://www.edd.ca.gov/taxrep/de231sk.pdf. For an analysis of options granted and data available on option values, see Oyer and Schaeffer (2002).

It is important to emphasize that the LEHD data capture nearly the full universe of covered employers and workers; they are not merely a sample of software workers or firms. However, when we look at certain specific features of workers or firms in the software industry, our data set becomes a smaller sample of the population of workers and firms. Our basic universe of data follows 83,497 employment spells of workers who were employed in the software industry in ten states in the U.S. between approximately 1992 and 2001 (the exact starting years vary by state). This length of time enables us to construct sufficiently long worker employment and earnings histories to address our research questions.

Our primary results are based on two analytical datasets, one consisting of 51,589 employment spells and one of 26,276 spells. These smaller samples are based on a number of restrictions aimed at isolating sets of firms and workers well suited to studying the precise connection between product market strategies and compensation policies. First, we limit the data to workers between the ages 21 and 44 in order to model the demand for a fairly homogeneous collection of individuals in the prime of their careers with similar educational vintages. This reduces the sample from 83,497 to 67,452.

Second, we limit we limit our data to those software workers earning more than an annualized $50,000 (in 2001 dollars) at the end of their 1997 job spell. We focus on software industry spells that span 1997 because software firms in existence that year are most readily matched to the 1997 Economic Census. The rationale behind the earnings threshold is that LEHD data do not contain information on hours of work or occupation. Therefore, to limit the data to workers who are likely to be full-time and in more highly skilled occupations, we choose those making more than $50,000. We choose the precise threshold based on a close analysis of the distribution of earnings within the relevant set of software occupations (programmers, developers, engineers, and managers) using PUMS data.[53] Together, the age and earnings restrictions reduce the sample to 51,589 spells.

While we could successfully match most businesses in our sample of workers to the Economic Census for 1997, a smaller subset had complete information on firm size, age, sales, and detailed product lines. There are 26,276 spells for which we have complete information on firm characteristics as well as worker characteristics. All told, 688 unique software firms appear in this sample.[54]

Lastly, we construct a subset of data of employees in high-skilled professions based on occupational information in the 2000 Decennial Census confidential long-form survey records. For this sample, we limit our data to those individuals in the software industry whom we can successfully match to the long-form and whom we can identify as software engineers, developers, or managers (irrespective of earnings). We drop those workers in other occupations within the software industry. Because the Decennial Census is a one in six sample of the population in 2000, this sample consists of only 2,638 workers. We use this dataset to check the robustness of our main findings, but due to its

[53] The primary occupations on which we focused included Census industry occupation codes 100 (Computer and Information Scientists, Research), 101 (Computer Programmers), and 102 (Computer Software Engineers, Applications and Systems Software), as well as 001-043 (managerial occupations).

[54] Throughout this chapter, when we refer to a firm, we are referring to a firm defined at the State Employer Identification Number (the SEIN, or UI account number), which is the unit of observation in the UI-Wage data. It is an 11-digit number used for reporting taxes at the state level. For single-unit firms, this reflects the entire firm, but for multi-unit firms, the SEIN reflects activity of the firm within a given state. We are able to match the workers to information in to the Economic Censuses since the UI files also include the federal Employer Identification Number (the EIN is on the ES-202 data that is part of the related administrative data system). The EIN is a nine-digit number assigned by Internal Revenue Service (IRS) and used for federal tax purposes by employers, sole proprietors, corporations, partnerships, non-profit organizations, trusts, estates of decedents, government agencies, certain individuals, and other business entities.

small size and the confidentiality of the data, we refer to the results using this sample largely in footnotes in the empirical analysis.

2.4.3 Measurement

2.4.3.1 Earnings Levels and Growth

As previously discussed, a major benefit of the LEHD data is that they are longitudinal in both workers and firms. In other words, the data have information about spells of employment with a firm and the associated earnings over long stretches of time. These unique data permit us to capture multiple facets of workers' earnings profiles. In modeling the link between product markets and compensation, we use information on earnings levels for new and experienced workers within firms, workers' earnings trajectories within firms, and earnings growth associated with transitions between firms.

We focus on four measures of earnings levels in the empirical analysis. One measure is beginning-of-spell earnings, which corresponds to a given worker's total earnings in the first full quarter of employment with an employer (with dollar values at annualized 2001 dollars).[55] Beginning-of-spell earnings include the earnings of new hires as well as the earnings of left-censored job spells in our data.[56] The next measure is end-of-spell earnings, which represents a worker's last full quarter of real annualized earnings in a given job spell. Our end-of-spell measure captures the earnings of workers leaving the firm as well as right-censored job spells, and it potentially contains exercised stock

[55] Throughout the analysis, we use full-quarter earnings, which represent earnings for workers who have been employed by the same employer for a entire quarter; that is, it represents earnings for a worker whom we observe at a firm in quarter t, t-1, and t+1. While this does not rule out part-time work, it does rule out obviously truncated quarters.
[56] Sixteen percent of the beginning-of-spell earnings are censored.

options.[57] Another measure, which is less likely to include exercised stock options, is earnings one year prior to the end of the spell (or starting earnings if the spell was less than one year long).[58] Finally, for those workers for whom we observe a prior spell, we measure the level of earnings in the last full quarter of their prior jobs.

We also use two measures of earnings growth. Earnings growth within the firm, or within-job earnings growth, is the difference between end-of-spell and beginning-of-spell earnings.[59] Between-job earnings growth is the difference between earnings in the first full quarter of a given worker's new software job and the last full quarter of his or her prior job.[60]

2.4.3.2 Product Market Payoff Dispersion

Testing the main implications of our model requires estimates of the variance of the expected payoffs of projects in the product market(s) in which each firm operates. For the prepackaged software industry, the 1997 Economic Census delineates 30 detailed product lines, ranging from consumer game and entertainment software to business graphics design and layout software to vertical industry banking software to mainframe computer applications. Firms in the Economic Census are asked to provide data on their revenue for each of the 30 product lines, and we exploit this information in order to

[57] Forty percent of the end-of-spell earnings are censored.
[58] Heath et al. (1999) find that while employees' option exercise is concentrated toward the end of their tenures when their grants are on the cusp of cancellation, they are also positively related to previous short-term stock returns.
[59] More specifically, within-job earnings growth is defined as log annualized end-of-spell earnings less log annualized beginning-of-spell earnings, divided by the number of full quarters that a worker was on the job.
[60] More specifically, between-job earnings growth is defined as log annualized beginning-of-spell earnings in the new job less log annualized end-of-spell earnings in the old job, divided by the number of full quarters between jobs. Clearly, between-job earnings growth is only defined for those individuals in the sample for whom we observe them in a job prior to their software job (i.e., those whose software jobs are not left censored and those who are not recent entrants or re-entrants into the labor market).

construct a firm-specific measure that reflects the variance of payoffs in each product category.

We create each firm's product payoff dispersion measure in two steps. First, for each of the 30 product classes, we calculate the 90-50 difference of the log of revenue per worker across all firms in SIC 7372 in the U.S. economy. Because some of these firms produce and sell multiple software products, we treat each product within each firm as though it were a separate revenue stream, assuming due to data limitations that revenue per worker is constant across product lines within each firm. Second, for each firm, we calculate payoff dispersion in the product markets in which it operates by weighting the product-specific 90-50 differences for the 30 products by the share of revenue that the firm derives from each product class. More specifically, we construct the firm-specific product payoff dispersion measure as

$$\textit{product payoff dispersion}_j = \sum_{k=1} (\textit{revenue share}_{jk})(\textit{product revenue dispersion}_k)$$

where *revenue share*$_{jk}$ is the share of firm j's revenue coming from product class k, for product classes $k = 1, 2, \ldots, 30$. The dispersion specific to product k is captured in *product revenue dispersion*$_k$. Again, we calculate the latter term as the 90-50 difference in log revenue per worker across all business entities in the software industry producing in product class k, where we treat each product class within each software firm as if it were its own independent entity.

Values of the product revenue dispersion measure for the product lines with the greatest and least dispersion appear in Table 2.3. The results suggest that there is substantial variation in the skewness of revenues across product classes, implying a high degree of heterogeneity in the degree of risk firms face in product markets even within the narrowly defined industry of software. Further, observed patterns of dispersion across different product lines are in line with expectations, with categories such as video games topping the list of product lines with high payoff dispersion and database and distribution software falling near the bottom.

Table 2.3: Software Industry Product Line Revenue Dispersion
SIC 7372

Product Line Code	Product Line Description	90-50 Ratio of Product Line Log Revenue per Worker
Product Lines in Software with Greatest Potential Payoffs/Risks		
1122	Game and Entertainment Software	1.31
1183	Networking Software	1.17
1123	Home Productivity Software	1.03
Product Lines in Software with Smallest Potential Payoffs/Risks		
1161	Banking and Finance Software	0.66
1142	Distribution Software	0.57
1184	Database Software	0.55

Based on 1997 Economic Census data for a national sample of firms.

There are several features of the firm-specific product payoff dispersion measure worth emphasizing. First, this variable reflects each firm's actual product mix, not its actual revenue. That is, the payoff measure reflects the skewness of revenue per worker in the product class(es) in which the firm operates as opposed to its actual revenues per worker. Thus, a firm with a high product payoff dispersion measure is not necessarily a high or low performing business, but rather has a product mix with a more highly skewed distribution of potential payoffs. Also notably, we use the 90-50 difference as the measure of dispersion in a given product line because the 90-50 difference captures skewness specifically in the upper tail of the payoff distribution. While our model refers to the variance of the entire distribution (the lower tail as well as the upper tail), we focus on the upper tail because we do not observe firms' losses – revenues are truncated at zero.

2.5 Empirical Approach

The model in Section 2.3 implies that firms operating in product markets with highly dispersed payoffs will structure their compensation schemes in efforts to attract and retain more highly talented workers. Our core empirical specification for addressing the predictions of the model is based on the following wage equation:

$$(1) \qquad ln(w_{ij}) = \boldsymbol{X_i\beta} + \boldsymbol{Z_j\delta} + \alpha\sigma_j^p + \varepsilon_{ij}$$

where w_{ij} is annualized earnings for worker i at firm j (measured at some observed point of the employment spell), $\boldsymbol{X_i}$ is a vector of worker controls, $\boldsymbol{Z_j}$ is a vector of firm controls, σ_j^p is the payoff dispersion or variance that firm j faces in its product market(s), and ε_{ij} is an error term.

Several issues are important to bear in mind in the empirical estimation of equation (1). First, as previously mentioned, our data include the wage histories for all workers who had job spells ongoing in the software industry in our sample in 1997. Also as previously noted, to focus on software programmers, engineers, and managers with similar educational vintages and at similar stages in their careers, we use workers who are between the ages of 21 and 44 and who earn at least $50,000 at the end of these ongoing spells.

In using this sample to estimate (1), we consider real annualized earnings observed at particular points in the job spell, including at the beginning of the spell, at the end of the spell, one year prior to the end of the spell, and at the end of the prior job spell. We control for right censoring and left censoring by including censoring dummies interacted with the full set of worker controls. The latter include quadratics in tenure in the job, tenure in the industry, and age, all of which are fully interacted with each other (as well as with the censoring dummies). While the set of worker controls is limited, restricting attention to 21-44 year-old workers earning at least $50,000 implies, as we previously discussed, that we are largely capturing individuals in the relevant educational and occupation categories.

For the firm controls, we include for each firm a quadratic in (log) employment; dummies for age; its employment growth rate; and a dummy for whether it is in a high density, high education, and industrially diversified county. We also include in the firm controls log revenue per worker and the rate of worker churn. All firm variables measured in 1997. The size, age, and growth controls are intended to capture other factors that might influence the rent sharing with workers in an indirect manner, while log revenue per worker is included as a control to account directly for rent sharing associated with actual outcomes. Worker churn at a firm, which we measure as the worker accession rate plus the separation rate less the absolute value of net employment growth, acts a control for riskiness on the labor market side. We discuss the role of this control as well as other aspects of our specification that take different dimensions of risk into account below.

In the empirical analysis, we consider a number of alternative versions and refinements of the benchmark specification (1). One incorporates the idea that wages should be more sensitive to the firm's payoff dispersion for more highly skilled workers. In the software industry, the top talent should command the highest premium in firms that operate in product markets with relatively high potential payoffs. By contrast, pay for low-wage workers should not be a function of the firm's product payoff dispersion, as worker sorting in the lower echelons of the skill and earnings distributions is less relevant. We explore this idea by supplementing OLS results from estimating (1) with results using quantile regressions, hypothesizing that the impact of payoff variance should be greater at higher percentiles of the earnings distribution relative to lower percentiles, conditioning on other worker and firm characteristics.[61]

Another refinement of the model involves a closer examination of the impact of more variance in potential payoffs on earnings growth as opposed to just earnings levels. There are a number of reasons why our current model would predict that firms in riskier product markets would offer high base pay that also rises sharply with tenure. Such firms might offer higher base pay because they value skills or talent more than other firms, and hence structure starting salaries so as to expand the pool of applicants and thereby ensure they can acquire the most talented people. Similarly, we would expect that pay should rise with tenure due to sorting; as in all matching models, the return to tenure would be high because firms both retain stars and pay them more over time. On the other hand, firms that place a high premium on talent would more readily fire workers who do not

[61] As another example of this technique, Buchinsky (1994) shows that the returns to education are higher at high wage quantiles, while the returns to experience are lower at high wage quantiles. Also, Hallock et al. (2004) show that among CEOs, the sensitivity of wages to firm performance rises as one moves up the earnings distribution.

meet their standards given the severe consequences of poor choices with respect to project development.

There are a number of other reasons to expect wages to increase with tenure among firms operating in riskier product markets. For one, firms in high-risk markets may invest more heavily in the human capital of their employees in light of the high returns to good project selection. Also, firms in high variance product markets may pay more for effort, in effect offering relatively steep incentive pay contracts.[62] Variation across firms in different product lines in the importance of teamwork is another reason we might expect wages to rise over time differentially; if people are working in teams in which their skills are likely to be complementary with the other team members in some environments more than others, some employers may take longer to identify and reward individual talent. Lastly, whether because they want to preserve a team at least through a given product cycle, reduce churning, or provide incentives for effort, many software firms intentionally tie employees down by granting stock options that vest slowly. In sum, firms operating in product markets associated with greater risk likely pay more for loyalty, compensating their employees for staying more so than firms in less risky product markets. As previously discussed, we have at our disposal several different measures of earnings levels and earnings growth rates that we can use to disentangle these effects empirically.

One concern is that a positive coefficient on σ_j^p in (1) and the related specifications might simply reflect a compensating differential for risk rather than a firm strategy designed to attract and retain talented workers. The presence of such differentials

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[62] Case study evidence suggests that some firms offer such contracts. Russell (2005) finds that a larger percentage of a given workers' pay is performance-based as the worker's skill level rises.

would imply that firms operating in high variance product markets seeking to induce high performance among employees would offer incentive contracts that involve low base or starting salaries but high performance-based pay. Firms in lower risk markets, on the other hand, would be expected to offer higher base pay with little possibility for growth if the worker or company performs well.

By contrast, our model states that firms operating in high variance product markets will want to select the highest quality workers, not necessarily those willing to shoulder the most risk. As a result, such firms will have higher starting salaries than firms in low-variance product markets. Hence, with starting salaries as the dependent variable, a positive coefficient on σ_j^p in (1) and in the related specifications is likely to reflect a return to skills, not a return to risk taking.[63] With earnings observed later in a given job spell as the dependent variable, though, a positive coefficient could at least in part reflect a return to risk taking (assuming the worker had taken a lower starting salary with the hope of future uncertain gains).[64] Yet the inclusion in each specification of a control for worker churning at the firm, which one can interpret as a control for job security,

[63] A firm's losses could harm a worker if that worker is fired or the firm fails; in each case, a worker may suffer losses in earnings and sacrifice any accumulated firm-specific human capital. However, this too should produce a compensating risk differential for experienced workers, not for young workers who have yet to invest in firm-specific skills. Also, Russell (2005) finds that within the firm, pay levels, bonuses, and options are highly correlated across individuals, reflecting the fact that more able workers have higher pay of every kind than less skilled workers.

[64] Under some circumstances, we might expect there to be less incentive pay in firms operating in high variance product markets. Indeed, in a tournaments model of incentive pay, increasing the amount of noise or luck reduces the use of incentive pay (Lazear and Rosen 1981). In our model, variance in payoffs could arise in part from idiosyncratic shocks representing noise or luck, but it also arises because some firms hire more talented people who select more successful products and should have pay tied to performance. In the data, we cannot identify whether the variance in the payoff arises from luck or effort, but our model of innovation proposes that it is high skill that produces high payoffs, so the coefficient σ_j^p should be positive as opposed to negative. Prendergast (2000, 2002) also points out that higher risk environments may have more performance-based pay because the cost of determining what inputs to monitor in such environments is greater. Since we cannot identify the source of the variance in payoffs and we do not have time-series data on product-specific variances or firm-specific variances, we turn to the data to determine the sign. For related empirical models of risk-pay incentive relationships, see Baker and Hall (2004), Core et al. (2003), Ittner et al. (2003), Murphy (1986), Schaefer (1998), and Wulf (2005). For excellent reviews of the literature on the subject, see Hallock and Murphy (1999) and Murphy (1999).

mitigates concerns that a positive coefficient on σ_j^p might reflect merely a compensating risk differential. Moreover, we consider alternative specifications that exploit workers' earnings on their prior jobs, reasoning that if firms are paying for talent rather than risk-taking, it should be reflected in individuals' earnings histories.

2.6 Empirical Results

2.6.1 Earnings Levels

The wage regression results in Table 2.4 explore the relationship between software worker earnings levels and the riskiness of the product markets in which firms in the industry operate. Again, product market risk for each firm represents the revenue-weighted 90-50 percentile difference in log revenue per worker across all firms that operate in the same product markets. We examine the impact of product payoff dispersion on mean earnings for software workers at various points in the job spell in the first column, then turn to an investigation of the impact at various percentiles of the earnings distribution in subsequent columns.

Table 2.4: Earnings Level Regression Results

	OLS	10th Percentile	50th Percentile	90th Percentile	95th Percentile
	(a) End-of-Spell Earnings - "Experienced Earnings"				
Product Payoff Dispersion	0.3868	0.0537	0.1203	0.8279	1.0215
	(0.0629)***	(0.0340)	(0.0397)***	(0.0990)***	(0.1341)***
Log Revenue per Worker	0.1360	0.0349	0.0996	0.1906	0.2241
	(0.0102)***	(0.0055)***	(0.0064)***	(0.0186)***	(0.0279)***
Firm Average Worker Churn	1.8940	0.5522	1.5728	2.1794	2.6960
	(0.1974)***	(0.1209)***	(0.1247)***	(0.3175)***	(0.4204)***
R-Squared	0.26	0.05	0.09	0.31	0.37
Number of Observations	26,276	26,276	26,276	26,276	26,276
	(b) Beginning-of-Spell Earnings - "Starting Salaries"				
Product Payoff Dispersion	0.0526	-0.1848	-0.0141	0.2129	0.3527
	(0.0331)	(0.0460)***	-0.0331	(0.0557)***	(0.0860)***
Log Revenue per Worker	0.0651	0.0399	0.0603	0.0578	0.0707
	(0.0053)***	(0.0075)***	(0.0053)***	(0.0095)***	(0.0152)***
Firm Average Worker Churn	0.6201	0.3002	0.4667	1.6007	2.1551
	(0.1029)***	(0.1499)**	(0.1031)***	(0.1628)***	(0.2411)***
R-Squared	0.18	0.10	0.11	0.11	0.12
Number of Observations	26,276	26,276	26,276	26,276	26,276

Table 2.4 (continued): Earnings Level Regression Results

	OLS	10th Percentile	50th Percentile	90th Percentile	95th Percentile
		(c) End-of-Prior Spell Earnings			
Product Payoff Dispersion	0.1840	0.1145	0.1734	0.1406	0.1702
	(0.0563)***	(0.1149)	(0.0516)***	(0.0722)*	(0.1072)
Log Revenue per Worker	0.0520	0.0571	0.0470	0.0342	0.0380
	(0.0103)***	(0.0208)***	(0.0094)***	(0.0123)***	(0.0177)**
Firm Average Worker Churn	0.7319	0.1743	0.6640	1.8479	1.8208
	(0.1911)***	(0.4089)	(0.1754)***	(0.2278)***	(0.3238)***
R-Squared	0.28	0.22	0.15	0.14	0.13
Number of Observations	10,803	10,803	10,803	10,803	10,803
		(d) Lagged (One Year) Earnings			
Product Payoff Dispersion	0.1312	-0.1674	-0.0759	0.4983	0.7846
	(0.0518)**	(0.0445)***	(0.0349)**	(0.1001)***	(0.1512)***
Log Revenue per Worker	0.1035	0.0476	0.0805	0.1395	0.1353
	(0.0084)***	(0.0069)***	(0.0057)***	(0.0184)***	(0.0300)***
Firm Average Worker Churn	1.6789	0.2986	1.4020	2.6819	3.1453
	(0.1627)***	(0.1499)**	(0.1097)***	(0.3194)***	(0.4971)***
R-Squared	0.17	0.07	0.08	0.17	0.22
Number of Observations	26,276	26,276	26,276	26,276	26,276

Worker controls include quadratics of tenure at job, tenure in industry, and age, fully interacted with each other and with appropriate left and right censoring dummies. Firm controls include a quadratic in (log) firm employment, dummies for firm age (<6 years, 6-10, 11+ years), the net employment growth rate, and a dummy for whether the firm is in a high density/high education/industrially diverse county. Controls also include time dummies for quarter of separation and/or quarter of accession as appropriate.

R-Squareds for OLS regressions are unadjusted; R-Squareds for quantile regressions are one minus the sum of weighted deviations about the estimated quantile divided by the sum of weighted deviations about the raw quantile.

Standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Based on LEHD data for ten states.

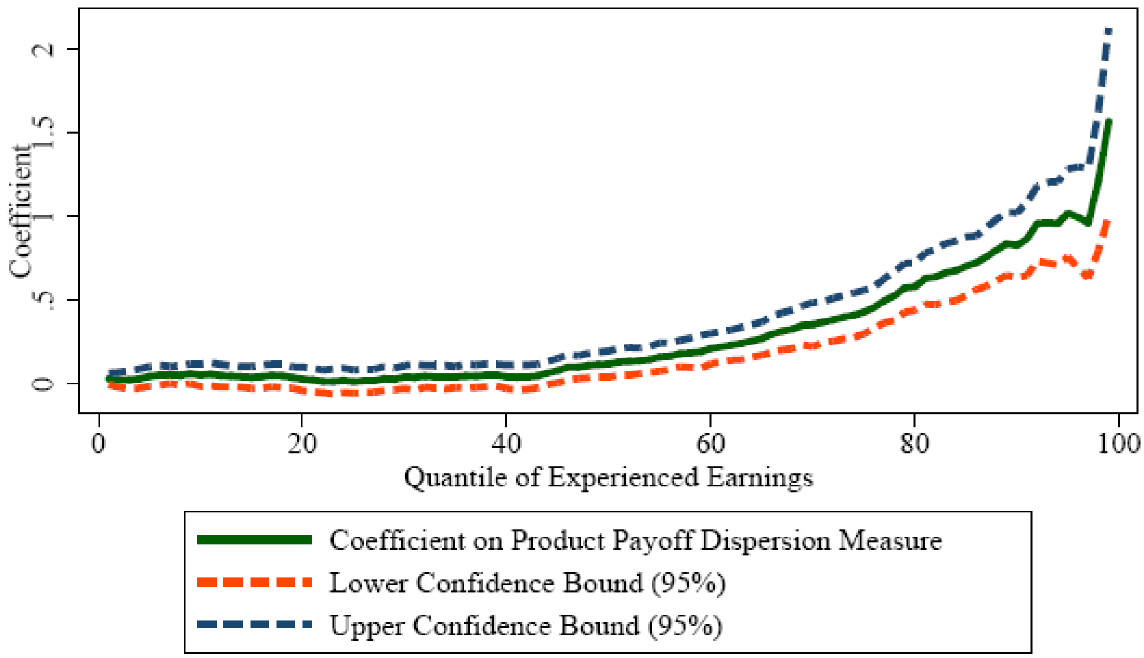
Looking first at the regression results in panel (a) of Table 2.4, it is clear that the product payoff dispersion variable has a very significant positive effect on end-of-spell (or experienced) earnings at the mean and at the top percentiles of the earnings distribution. A perusal of the columns of panel (a) suggests that the impact of the product payoff dispersion measure rises sharply with skill level, and indeed the differences between coefficients on product payoff dispersion at the lower and upper ends of the distribution are highly significant. For example, an F-test for the equivalence of the 10th and 90th percentile product payoff dispersion coefficients based on the full covariance matrix of the estimators from the simultaneous quantile regression (with estimates of variance obtained by bootstrapping) yields an F-statistic of 39, indicating that we can reject the null hypothesis at the 1% level.[65] In other words, software workers at the upper reaches of the earnings distribution gain the most from working at firms in product markets characterized by greater risk.[66]

[65] Based on 50 bootstrap repetitions. A 95% confidence interval for the difference between the 90th percentile and the 10th percentile coefficient on product payoff dispersion is [0.53, 1.02]. While the differences between the coefficients at the 10th and 95th percentiles, the 50th and 90th percentiles, and the 50th and 95th percentiles are also significant at the 1% level, the differences between the coefficients at the 10th and 50th and the 90th and 95th are not. Varying the number of bootstrap repetitions has little effect on the standard error estimates, and estimates from the bootstrap model differ little from the analytic estimates we present in the tables.

[66] Hallock et al. (2004) point out that "higher ability managers [would have] higher pay for performance incentives than low ability managers" (7) due to the lower cost of effort for high ability managers.

Figure 2.3, which plots the coefficient on σ_j^p at each percentile of the earnings distribution, illustrates the sharply increasing impact of product payoff dispersion for these experienced workers.

Figure 2.3: Effects of Product Payoff Dispersion across the Earnings Distribution
Experienced Earnings



Worker controls include quadratics of tenure at job, tenure in industry, and age, fully interacted with each other and with appropriate left and right censoring dummies. Firm controls include a quadratic in (log) firm employment, dummies for firm age (<6 years, 6-10, 11+ years), the net employment growth rate, and a dummy for whether the firm is in a high density/high education/industrially diverse county. Controls also include time dummies for quarter of separation and/or quarter of accession as appropriate.
Based on LEHD data for ten states.

The magnitudes of the effects of product payoff dispersion in Table 2.4 and Figure 2.3 are sizable. Holding all other controls fixed and using the product line dispersion statistics from Table 2.3, workers at the 50th percentile employed at a firm producing a product with the highest payoff risk would have end-of-spell or experienced earnings that are 9% higher than if they were employed at a firm producing a product with the lowest risk. This differential jumps to 63% at the 90th percentile, and further grows to 77% at the 95th percentile.[67]

For beginning-of-spell earnings, results for which appear in panel (b) of Table 2.4, the impact of the product payoff dispersion measure is positive (albeit not highly significant) at the mean. However, it is positive and significant at the 90th and 95th percentiles, suggesting that even among new hires, firms operating in product markets with greater variance in potential payoffs pay higher wages. This, in turn, implies that firms in the industry that face greater risk in the product market may be more actively seeking to select talented, highly skilled workers.[68]

These results are consistent with not only the model in Section 2.3, but also extensive industry testimony that describes the software industry's very careful and deliberate hiring practices, all aimed at identifying the right talent and reflecting the high-commitment work environment of the industry (Hoch et al. 2000). Meanwhile, the results for starting salaries are not consistent with the notion that firms pay a compensating wage differential for risk taking among workers, in which case we would expect a negative as opposed to a positive coefficient on the dispersion measure. To the extent that we can interpret prior spell earnings as a proxy for skill, the results in panel (c) of Table 2.4 further undermine the argument that compensating wage differentials are driving the

[67] In interpreting the results in terms of magnitudes, it is important to emphasize that the reported effects from the quantile regressions yield the implied effect of the variable in question on the conditional quantile distribution. The conditional quantile distribution is the distribution of earnings taking into account all the other explanatory variables. Thus, the reported coefficients do not yield inferences about the impact of variables on the unconditional distribution of earnings. For our purposes, the focus on the conditional distribution of earnings is appropriate since we are interested precisely in the impact of product payoff dispersion holding the impact of all other factors constant. For further discussion of these issues, see Buchinsky (1994).

[68] F-tests for beginning-of-spell earnings indicate that we can reject at the 1% level the equivalence of the product payoff dispersion coefficients at the 10th and 50th percentiles, the 10th and 90th percentiles, the 10th and 95th percentiles, the 50th and 90th percentiles, and the 50th and 95th percentiles. The difference between the coefficients at the 90th and 95th is not significant at the 1% level.

results and lend more support to our model; the positive coefficient on product payoff dispersion for prior spell earnings indicates that high-risk firms recruit the most skilled workers, not merely those willing to bear greater risk.

A comparison of the results in Table 2.4 for experienced earnings (panel (a)) and for starting earnings (panel (b)) suggests that earnings are much more sensitive to product payoff dispersion for experienced workers than for new hires. Moreover, as the earnings figures in Table 2.1 suggest, rewards for experienced workers can be huge. Indeed, 10% of software workers earn more than $310,000 at the end of their spells. The very high compensation for experienced workers could reflect a number of factors, including higher marginal products (as in our model), a tournament reward structure, participation in a high-performance team, or improved selection of talented workers over time in the firm. We cannot distinguish among these alternatives with our data, but Russell (2005) provides very detailed evidence for one software company that suggests that all of these factors may enter the earnings of software workers.[69] In any case, however, the individual who can create or select the best projects will have more skills and more incentive pay in firms with high product payoff dispersion.

The regression results for experienced workers (panel (a) of Table 2.4) may be influenced by the inclusion of exercised stock options in the earnings measure. To test the sensitivity of our results to the inclusion of options and any other compensation that might only be realized at the end of workers' job spells, we run an additional regression in which experienced earnings are redefined as those for people one year before they quit

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[69] All indications are that the firm in Russell's (2005) study looks very much like the typical large firm in our data. The median age among workers is 33, and tenure ranges from 2.7 to 3.1 years over 1996 to 1999. About 65% of workers were in research and development and 30% were in management or administration. These figures are very consistent with the age, tenure, and occupational profile of the workers in our sample.

their job or prior to dropping out of our sample due to censoring. As the results in panel (d) of Table 2.4 reveal, although the point estimates of the impact are smaller than for end-of-spell earnings, the same basic results hold when we use lagged earnings as the dependent variable. Indeed, as one might expect, the coefficient estimates in panel (d) for product payoff dispersion at the mean and across the distribution fall squarely between those in panel (a) and (b), hinting at the extent to which earnings grow increasingly sensitive over time to the degree of risk firms face in their product markets.

Several of the coefficients on the control variables in the regressions in Table 2.4 are of interest in light of our model. First, consider the effect of firms' actual revenues on the different earnings measures. The results in Table 2.4 show that, notwithstanding the earnings measure chosen, workers tend to earn more when their employers are successful; indeed, pay rises very significantly as a function of log revenue per employee.[70] Additionally, the quantile analysis in panel (a) suggests that experienced high-wage workers are paid disproportionately more when their firms thrive. This should be interpreted as a firm fixed effect; firms that are highly productive in 1997 (when we measure firms' revenues) pay more to workers in adjacent years as well.[71]

Also of note in Table 2.4, we find that pay is increasing in the amount of worker churning at firms. As we discussed earlier, the inclusion of worker churning as a control

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[70] Using end-of-spell earnings, F-tests indicate that we can reject at the 1% level the equivalence of the log sales per worker coefficients at the 10^{th} and 50^{th} percentiles, the 10^{th} and 90^{th} percentiles, the 10^{th} and 95^{th} percentiles, the 50^{th} and 90^{th} percentiles, and the 50^{th} and 95^{th} percentiles. The difference between the coefficients at the 90^{th} and 95^{th} is not significant at the 1% level.

[71] In interpreting these results, it is useful again to emphasize that, while the product mix payoff risk measure varies across firms, it is not driven by the realized payoffs of the firm but rather the potential payoff distribution based upon the pool of firms with that product mix. This feature substantially mitigates concerns of contemporaneous endogeneity of the payoff mix measure. This payoff risk measure does reflect a choice by the firm (i.e., the choice of product mix), but this choice is likely made either at the founding of the firm or, at the very least, is made infrequently. After controlling for firm performance, the effects of the product market payoff remain unchanged, which should further reduce concerns about endogeneity.

helps to capture effects that may be associated with compensating differentials for risk taking, since turnover can be thought of as a proxy for job security. That the main results are robust to the inclusion of this control provides yet more evidence that our finding that greater product payoff dispersion is associated with higher earnings reflects firms' efforts to attract and retain highly talented workers rather than to compensate for risk.

In sum, the OLS and quantile regression results in panels (a) through (d) of Table 2.4 indicate that software workers' earnings are higher when their employers operate in high variance product markets. The results suggest that this relationship reflects more than merely rent sharing by high-risk firms that might be more successful, as we control for individual firm performance. Critically, workers at the upper end of the earnings distribution are rewarded disproportionately when their employers operate in high variance product markets and when their employers succeed by achieving high revenues. These results are robust to using different measures of earnings and, as we find in unreported regressions,[72] to using different specifications with varying sets of control variables.[73]

[72] In separate regressions, we include end-of-prior spell earnings as a control variable in the end-of-spell, beginning-of-spell, and lagged earnings level regressions. This specification sheds light on the extent to which firms are hiring the best workers as opposed to offering a different schedule of wages for workers with a given level of talent. The results indicate that, even controlling for talent as proxied by end-of-prior spell earnings, those firms in product markets characterized by higher risk in terms of potential payoffs to innovation reward talent and loyalty more highly. That is, the coefficients on the product payoff dispersion measure are qualitatively similar with the inclusion of end-of-prior spell earnings as an additional independent variable.

[73] Also in unreported regressions, we find that the results are robust to subsetting the data to look only at individuals for whom we can identify their occupation using Decennial Census data. While limiting the size of our sample substantially, integrating occupation data from the Decennial Census permits us to exclude workers other than programmers, engineers, and managers in software firms. For workers outside these occupations, such as administrative and sales staff, we might expect the link between project success and compensation to be weak.

2.6.2 Earnings Growth

We next turn to examining the relationship between the nature of the product markets in which firms operate and the earnings growth workers experience both on the job and as they move between jobs. The main results on the impact of greater product payoff dispersion on within-job earnings growth are in line with the spirit of the model in Section 2.3 and echo the results using experienced earnings levels in Table 2.4. Indeed, as panel (a) of Table 2.5 reveals, within-job earnings growth rates rise sharply with the product payoff dispersion of firms, and the impact is greatest for workers at the highest earnings quantiles. For example, an F-test for the equivalence of the 10th and 90th percentile product payoff dispersion coefficients based on the full covariance matrix of the estimators from the simultaneous quantile regression yields an F-statistic of 55, indicating that we can reject the null hypothesis at the 1% level.[74]

[74] F-tests for within-job earnings growth indicate that we can reject at the 1% level the equivalence of the product payoff dispersion coefficients at the 10th and 50th percentiles, the 10th and 90th percentiles, the 10th and 95th percentiles, the 50th and 90th percentiles, and the 50th and 95th percentiles. The difference between the coefficients at the 90th and 95th is not significant at the 1% level.

Table 2.5: Earnings Growth Regression Results

	OLS	10th Percentile	50th Percentile	90th Percentile	95th Percentile
	(a) Within-Job Earnings Growth				
Product Payoff Dispersion	0.0706	-0.0060	0.0481	0.1837	0.2074
	(0.0120)***	(0.0073)	(0.0065)***	(0.0191)***	(0.0227)***
Log Revenue per Worker	0.0102	-0.0058	0.0037	0.0340	0.0471
	(0.0020)***	(0.0012)***	(0.0011)***	(0.0037)***	(0.0048)***
Firm Average Worker Churn	0.2283	0.1346	0.2489	0.3331	0.3824
	(0.0379)***	(0.0225)***	(0.0205)***	(0.0668)***	(0.0845)***
R-Squared	0.16	0.07	0.08	0.23	0.28
Number of Observations	26,276	26,276	26,276	26,276	26,276
	(b) Between-Job Earnings Growth				
Product Payoff Dispersion	-0.2169	-0.2352	-0.1725	-0.2597	-0.2215
	(0.0476)***	(0.0653)***	(0.0270)***	(0.0921)***	(0.1965)
Log Revenue per Worker	0.0188	0.0367	0.0195	0.0080	-0.0221
	(0.0087)**	(0.0116)***	(0.0049)***	(0.0164)	(0.0337)
Firm Average Worker Churn	0.2146	-0.1877	0.2511	0.2766	0.1832
	(0.1624)	(0.2353)	(0.0921)***	(0.3099)	(0.6815)
R-Squared	0.09	0.04	0.05	0.09	0.11
Number of Observations	10,803	10,803	10,803	10,803	10,803

Worker controls include quadratics of tenure at job, tenure in industry, and age, fully interacted with each other and with appropriate left and right censoring dummies. Firm controls include a quadratic in (log) firm employment, dummies for firm age (<6 years, 6-10, 11+ years), the net employment growth rate, and a dummy for whether the firm is in a high density/high education/industrially diverse county. Controls also include time dummies for quarter of separation and/or quarter of accession as appropriate.

R-Squareds for OLS regressions are unadjusted; R-Squareds for quantile regressions are one minus the sum of weighted deviations about the estimated quantile divided by the sum of weighted deviations about the raw quantile.

Standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Based on LEHD data for ten states.

By contrast, between-job earnings growth, results for which appear in panel (b) of Table 2.5, is not a function of the potential payoff of the firm. That is, while workers reap large returns in terms of earnings growth when they stay with firms that operate in product markets characterized by greater risk, the gains to job-hopping into such firms do not tend to be disproportionately large. For the median worker, the effect of product payoff dispersion for between-job earnings growth is actually negative and significant, though at higher earnings quantiles it is insignificant.[75] Thus, though beginning-of-spell earnings are higher for individuals working in firms operating in high variance product classes (panel (a) of Table 2.4), these firms do not appear to be offering any higher starting salaries to workers relative to their past earnings than other firms in the industry.[76]

To the extent that earnings on the prior job spell reflect workers' innate and accumulated skills, these findings are consistent with our model. In order to attract talented workers, firms that operate in riskier product markets are willing to pay higher starting salaries, but tend to do so more often for more experienced workers who have been successful in the past and therefore have higher prior spell earnings.[77]

Therefore, the results suggest that, while job-hopping for higher future earnings may be a common strategy, it is not the best short-term strategy for wage growth. In this sense, loyalty pays, as workers who stay with their employers tend to see stronger

[75] F-tests for between-job earnings growth indicate that we cannot reject at the 1% level the equivalence of the product payoff dispersion coefficients between any pair of percentiles we present in panel (b) of Table 2.5.

[76] The results for within-job and between-job earnings growth are qualitatively similar with the inclusion of end-of-prior spell earnings as an additional control variable.

[77] Since starting compensation does not include options granted, we may be underestimating the gains to job-hopping if software workers are moving between firms to achieve higher option grants. However, options granted are not yet compensation; an individual must typically stay with a firm four years to vest the options granted. Thus, even if options are granted with job change, the pay is only realized from within firm pay increases.

earnings gains over time. Moreover, the firms that reward loyalty the most are the very firms that operate in high-risk, and thus high potential payoff, product markets. We cannot assess precisely why loyal workers tend to reap the greatest rewards in firms in high-risk markets, and indeed the differential may arise due to factors ranging from variation across markets in the importance of teamwork, firm-specific human capital accumulation, monitoring costs, intellectual property protection, etc. In any case, the results make clear that loyalty in the software industry pays, and pays disproportionately among firms that face the riskiest product markets. Firms in these dynamic markets, therefore, structure compensation not only to select the most talented workers, but also to ensure they motivate and retain them.

2.7 Conclusion

The process of innovation in the U.S. economy is fundamentally dependent on employing and rewarding highly talented workers. This chapter highlights important relationships between the product market strategies and human resource practices of innovative firms. In particular, we show that software firms that operate in product markets with highly skewed returns to innovation, or high variance payoffs, are more likely to attract and pay for highly talented workers. Such firms do so first by paying more up-front in starting salaries to attract and motivate skilled employees, and second by rewarding talented workers handsomely for loyalty. These striking effects are robust to the inclusion of a wide range of controls for both worker and firm characteristics, including variables capturing rent-sharing opportunities and proxies for other types of risk.

Though we focus on the software industry, our model and findings should generalize to any industry in which firms employ knowledge workers and face uncertainty in the probability of success on any given project. Our results documenting a link between income variance and innovation also complement the literature on income inequality, changing skill demand, and economic growth. Recent research suggests that returns to skill have been increasing within as well as across occupations and industries, and furthermore that increases in earnings inequality in recent decades have been driven largely by changes in the upper as opposed to lower tail of the income distribution (Autor et al. 2003; Autor et al. 2005, 2006; Lemieux 2006b). Our results for the software industry speak to these broader patterns. We find that innovative high-technology firms pay a premium for talent, contributing to a highly skewed distribution of earnings. We cast this inequality in a positive light, showing how high variance in earnings goes hand-in-hand with innovative activity in dynamic and risky markets. To the extent that these markets have been and will continue to be a source of growth in the economy, our research makes important contributions to our understanding of not only firm human resource practices and product market strategies, but also patterns of income inequality and economic development.

Chapter 3

Decomposing the Sources of Earnings Inequality: Assessing the Role of Reallocation*

3.1 Introduction

Disentangling the sources of changes in earnings inequality has long been a challenge. The literature has provided both demand and supply side explanations, including, for example, skill-biased technological change, minimum wage adjustments, changes in workforce composition, and declines in unionization. Yet although wages are determined by the interaction of both firms and workers, most analytical work has been based on cross-sectional surveys of workers. As a result, little is known about the impact on the earnings distribution of changes over time in the types of firms and the allocation of workers across those firms.

In this chapter, we begin to fill this gap in the literature by using matched administrative data that contain longitudinal information on workers as well as on the firms for which they work. Our empirical work not only complements earlier worker-based studies that analyze changes in *within group* inequality by investigating *within industry* inequality, but also advances knowledge about the sources of changes in earnings inequality in several ways. First, it quantifies the impact of changes in workforce composition, particularly workforce skill and experience, on the earnings distribution by examining the reallocation of workers into and out of the workforce.

* This chapter draws on a joint paper with Fredrik Andersson, Elizabeth Davis, Julia Lane, Brian McCall, and L. Kristin Sandusky with the same title. The authors acknowledge helpful comments from Charlie Brown, David Card, Erica Groshen, and the participants of the labor lunch at the University of California-Berkeley.

Second, it tracks the reallocation of workers across jobs to reveal the earnings impact of changing firm wage premia, which could be attributable to variation in degrees of unionization, compensating differentials, or rent-sharing. Finally, it studies the impact of firm entry and exit, and the resulting job allocation, on the earnings distribution, providing commensurate insight into the impact of changing production processes. Because our interest is primarily in understanding the impact of changes in firms and the allocation of workers across firms rather than on changing industry structure, we examine each major industry separately.

In general, we find that there is no single “silver bullet” that explains changes in the earnings distribution in each industry. Even when the direction of change is similar across industries, the underlying contributing factors can be very different. Furthermore, even in industries in which overall inequality is trending in opposite directions, the influence of one set of factors can be consistently in the same direction.

Not surprisingly given the extensive amounts of worker reallocation and firm reallocation that occur both between and within industries, we find that both types of reallocation have large effects on different parts of the earnings distribution. In particular, the entry and exit of firms and sorting of workers and firms based on underlying worker skills are important determinants of changes in industry earnings distributions over time.

On the whole, new firms act to buttress earnings at the bottom end of the income distribution. However, at the same time, existing low-wage firms have expanded their share of employment of low-wage workers. The former result is consistent with the notion that new firms are more productive than old, while the latter is consistent with the fears of policymakers that there are fewer high-wage jobs available to low-wage workers.

Although our analysis focuses on the consequences of within-industry reallocation, these results suggest caution when searching for simple answers to questions raised by complex economic phenomena.

The chapter is structured as follows. After a brief review of the literature and discussion of the data, we present some basic empirical facts about the changes in the earnings distribution in each industry sector. We then develop an econometric method for decomposing the sources of change in earnings distributions using employer-employee matched data. The remaining sections of the chapter describe the results of performing these decompositions and summarize the implications.

3.2 Background

3.2.1 Earnings Inequality

Despite a vast literature that attempts to distinguish among the many possible sources of the increase in earnings inequality that occurred in recent decades in the U.S., there is still not complete consensus on its causes.[78] A large number of researchers agree that the change was driven by skill-biased technical change interacting in complex ways with changes in unionization, management structure, and international trade (e.g., Acemoglu 2002). However, there is some disagreement about the relative importance of labor market versus institutional factors in driving changes in the earnings distribution. Some researchers, such as Lemieux (2006a), point to changes in the composition of the U.S. workforce as an important contributor to recent shifts in the distribution of earnings. Others point to structural changes; for example, Card and DiNardo (2002) argue that changes in the minimum wage and declines in unionization were the principal

[78] For a recent survey of the wage inequality literature, see Autor and Katz (1999).

contributors to recent observed trends in inequality. Fortin and Lemieux (1997), meanwhile, highlight the impact of deregulation on changes in earnings inequality in the 1980s, focusing on the transportation, communication, and banking industries. Levy and Murnane (1992) as well as Danziger and Gottschalk (1995) provide excellent summaries of research on possible causes of observed changes in earnings inequality.

Notably, Autor et al. (2006) find that since the late 1980s, there has been a divergence in the change in wage inequality between the upper and lower halves of the wage distribution. The lower half of the distribution, as measured by the 50-10 difference in log wages, has changed little over time, while the upper half, as measured by the 90-50 difference, has exhibited a steady widening. They further find that labor force compositional shifts have acted to increase wage inequality, with the impact being an offset to countervailing wage compression movements in the lower half of the distribution and a reinforcement of residual wage inequality increases in the upper half of the distribution.

Nearly all of the empirical studies on wage inequality are limited to analyses of worker-based surveys, most notably the Current Population Survey (CPS). However, there is some evidence that suggests that changes in the distribution of wages may be due in part to changes on the firm side of the labor market. Bernard and Jensen (1998) find that increases in wage inequality across states are highly correlated with shifts in industrial composition, and in particular with the decline in manufacturing. Meanwhile, Burgess et al. (2001) observe marked differences in trends in earnings inequality across industries in Maryland. Other studies have also established the role of firm effects on wages and on wage inequality. For example, Davis and Haltiwanger (1991) find that firm size is an important determinant of wages, and that wage inequality has shifted both among and within manufacturing plants. Also using longitudinal employee-employer matched data, Abowd et al. (1999) investigate the interaction between high-wage firms, or firms that seem to pay a wage premium or markup, and high-wage workers, or those who earn a more than we would expect given their observable characteristics, most likely as a return to unobserved skill.

3.2.2 Worker and Firm Reallocation

The approach we take in this chapter differs from that taken in most studies on changes over time in earnings inequality. Often, researchers seek to untangle the relative contribution of different factors on changes in inequality using a time series of cross-sectional datasets. However, an important paper by Gottschalk and Moffitt (1994), which examines changes in earnings for individuals in the Panel Study of Income Dynamics, decomposes earnings into a permanent and a temporary component and finds an important role for each. This implies that we cannot paint a complete picture of how changes in the earnings distribution arise without data that permit us to track individuals over time. Further, given the extent of firm reallocation in the economy as well as well-documented relationships between industrial structure and earnings, access to information on the firms at which individuals are employed is also potentially critical in understanding changes in the distribution of wages.

By exploiting longitudinal employee-employer matched data in this study, we can focus on the impacts of variation over time in the types of workers, the types of firms, and the sorting of firms and workers on changes in the earnings distribution. These results, in turn, can shed light on the relevance of different hypotheses regarding the sources of changes in inequality. For example, changes in workforce composition that lead to an increasingly skilled workforce would be consistent with demand-side explanations such as skill-biased technological change. Similarly, firm entry and exit that lead to high premium firms replacing low premium firms can be linked to firm learning and selection of new technologies, and worker sorting effects can be tied to changes in the productivity of matches between individuals and firms (Jovanovic 1982, Ericson and Pakes 1995, Haltiwanger et al. 2007). Changing sectoral earnings inequality in low-wage and highly unionized industries would be consistent with hypotheses about the impact of institutional factors such as real minimum wages and changing unionization.

There is strong evidence that there exist sufficient turbulence in workforce composition, in firm composition, and in the reallocation of workers to drive changes in industry earnings distributions over time. The potential to change even the most stable workforce at the firm level over a decade or more is quite substantial. Burgess et al. (2000) point out that after nine years, only 42% of workers are still employed by the same employer in non-manufacturing; in manufacturing, the percentage is an even lower 32%. In addition, there is ample room for changing firm and industry structure to alter the economic landscape. Davis et al. (1996) document the large magnitude of job creation and destruction and highlight the dominance of idiosyncratic factors in accounting for the observed rapid pace of job reallocation. Meanwhile, Spletzer (2000) reports that 40% of new businesses die within three years of their birth, and that more than half of all jobs destroyed in a three-year period are due to the death of establishments. Recent work, including, for example, Foster et al. (2005), also suggests that in the course of this reallocation, more productive firms tend to replace less productive ones.

3.3 Data

A database created and maintained by the Longitudinal Employer and Household Dynamics (LEHD) Program at the U.S. Census Bureau makes our approach to decomposing the sources of changes in earnings inequality over time possible. These data enable us to match workers with past and present employers, together with employer and worker characteristics. This database consists of quarterly records of the employment and earnings of almost all individuals from the unemployment insurance (UI) systems of a number of U.S. states in the 1990s.[79]

These data have been extensively described elsewhere (Abowd et al. 2004), but it is worth noting several advantages they hold over household-based survey data. The data are current, and the dataset is extremely large. Since the scope of the data is nearly the universe of employers and workers in the covered private sector, it is possible to trace the movements of workers across earnings categories and across employers.[80] The UI records have also been matched to internal Census survey data and other administrative records to obtain basic demographic information including workers' date of birth, place of birth, race, and gender.

Of particular importance given the focus of this study is the reasonably accurate reporting of both earnings and industry. A recent paper by Hirsch and Schumacher (2004) points out that as many of 30% of respondents to the CPS do not respond to income questions, and consequently have imputed income information. In the LEHD data, earnings are very accurately reported since there are financial penalties for firms for

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[79] Because of the sensitivity of these data, the records are anonymized before they are used in any Census Bureau projects. Any research that is engaged in must be for statistical purposes only, and 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.

[80] Stevens (2002) describes coverage issues related to the LEHD database.

misreporting. In addition, there is substantial internal evidence from the LEHD Program that not only do workers often misreport earnings, but also that they do not correctly identify their industry, even at the major sector level (Decressin et al. 2006).[81]

Because almost all jobs in the covered private sector workforce appear in the LEHD dataset, we can analyze two different facets of the labor market, jobs and employment. The two differ to the extent that there is multiple job holding as well as to the extent that there is constant churning of workers through different sets of jobs. When we use workers as the unit of analysis, we typically describe their employment with their main (or dominant) employer over the year, and characterize that employer's industry, size, and turnover rates.[82]

Since we do not observe hours worked in the data but instead only observe quarters worked, we use log real annualized earnings as our primary measure of earnings. This measure represents, for each worker, the full-time, full-year earnings equivalent of the quarterly earnings information in the UI data, adjusted for discontinuities in labor market attachment during the year.[83] The final dataset includes year and sector specific

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[81] See Bound and Krueger (1991) and Bound et al. (2001) for further discussion of measurement error in longitudinal data.

[82] A worker's dominant employer is the SEIN (state employer identification number, which represents the state UI administrative unit) that contributes the most to the worker's earnings in each year. Thus, each worker employed during a year has one (and only one) dominant employer that year.

[83] More specifically, in order to calculate log real annualized earnings, we first define full-quarter employment in quarter t as having an employment history with positive earnings for quarters t-1, t, and t+1. Continuous employment during quarter t means having an employment history with positive earnings for either t-1 and t or t and t+1. Employment spells that are neither full quarter nor continuous are designated discontinuous. If the individual was full-quarter employed for at least one quarter at the dominant employer, the annualized wage is computed as four times average full-quarter earnings at that employer (total full-quarter earnings divided by the number of full quarters worked). Otherwise, if the individual was continuously employed for at least one quarter at the dominant employer, the annualized wage is average earnings in all continuous quarters of employment at the dominant employer multiplied by eight (i.e., four quarters divided by expected employment duration during the continuous quarters of 0.5). For the remaining small number of observations, annualized wages are average earnings in each quarter multiplied by 12 (i.e., four quarters divided by an expected employment duration during discontinuous quarters of 0.33). For additional definitions and details, see Abowd et al. (2002).

earnings statistics for workers whom we have identified as having a dominant employer that year, whom we impute to work full time that year, whom we have identified as likely working at the end of the first quarter that year, and who have (real) earnings of at least $250 in at least one quarter of the year.[84]

The LEHD database also includes new measures of human capital that we actively exploit in our analysis. Standard measures of human capital such as education and experience do not capture important variation across individuals in underlying ability and other unobserved factors that could affect earnings. Moreover, work by Juhn et al. (1993) demonstrates that a major contribution to increased earnings inequality in the 1980s was an increase in returns to "unmeasured" characteristics, such as interpersonal skills. The LEHD dataset permits the quantification of the value of these measures, although not permitting a decomposition of the sources (Abowd et al. 1999, Abowd et al. 2002). This is achieved by capturing the portable component of individual earnings, or that component that belongs to an individual as he moves from job to job in the labor market and that is separate from the type of firm for which he works.

Our chosen measure of human capital combines two elements, one associated with unobservable individual time invariant heterogeneity and one associated with time varying experience. In interpreting the human capital measure, several remarks should be made. First, the human capital measure is not simply a ranking of the wage of the worker,

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[84] We restrict attention to full-time workers, using data from the CPS in combination with LEHD state data to impute whether or not a worker is employed full time in each year at his dominant job. In addition, since the distribution of workers employed in a sector at a particular point in time may differ substantially from the distribution of all workers working in the sector at any time during the year, we obtain a "snapshot" of the earnings and human capital distribution in each sector by identifying those workers most likely working at a certain point in time, which we chose to be the end of quarter one of each year. This timing is consistent with the timing of the employment count reported by businesses in the Economic Census and other business surveys. For more discussion of imputation methods and restrictions on LEHD samples, see Abowd et al. (2006).

precisely because wages include both person and firm effects. Second, the measure will reflect the influence of any time-invariant personal characteristics, including unobserved dimensions of skill as well as observed accumulated skill correlates such as educational level.

At the same time, our measure of human capital abstracts from firm effects that may be present in measures based upon observable characteristics. Indeed, it will not reflect either firm-specific human capital or match effects, which we evaluate separately in our analysis. The firm effect literally captures the extent to which the firm to which the worker is attached pays above or below average wages (after controlling for person effects), and may reflect many factors including rent sharing, firm-specific human capital, compensating differentials, or unionization effects (Abowd et al. 2002, Andersson et al. 2005). Match effects, meanwhile, reflect changes in the joint distribution of unobserved worker attributes and firm pay policy, or the sorting of workers and firms.

In order to analyze the widest possible time interval (1992-2003) as well as to ensure computational feasibility given the large number of records in the data, we restrict our attention to four U.S. states, incorporating data from California, Illinois, Maryland, and North Carolina. In 2003, these four states accounted for approximately 21% of U.S. employment.[85]

[85] The fraction was computed using data from the CPS's Monthly Outgoing Rotation Group for 2003.

3.4 Descriptive Statistics

3.4.1 Changes in Earnings Inequality

We use the 1992-2003 difference in log real wages at different percentiles to illustrate changes in earnings distributions across industry sectors.[86] Table 3.1 shows for 2003 the 90th, 50th (median), and 10th percentile of earnings by sector as well as the 90-10, 90-50, and 50-10 log wage differences by sector. An examination of the first three columns of Table 3.1 reveals that there are substantial earnings differences across industries. For example, median earnings are over twice as high in mining as in agriculture, fishing, and forestry. The highest 90th percentile earnings are in the finance, insurance, and real estate sector, while the lowest 10th percentile earnings are in the retail trade sector. The distribution of earnings also varies across sectors, particularly at the upper end. The 90-10 log wage gap in 2003 is largest in services, but is also very high in finance, insurance, and real estate; wholesale; retail; and manufacturing. These same five industries also had the highest 90-50 log wage differences in 2003. In contrast, inequality at the lower end of the earnings distribution does not vary as much across industries, though services had the largest 50-10 log wage difference.

[86] We use the Standard Industrial Classification (SIC) to identify industry sectors and omit the public sector.

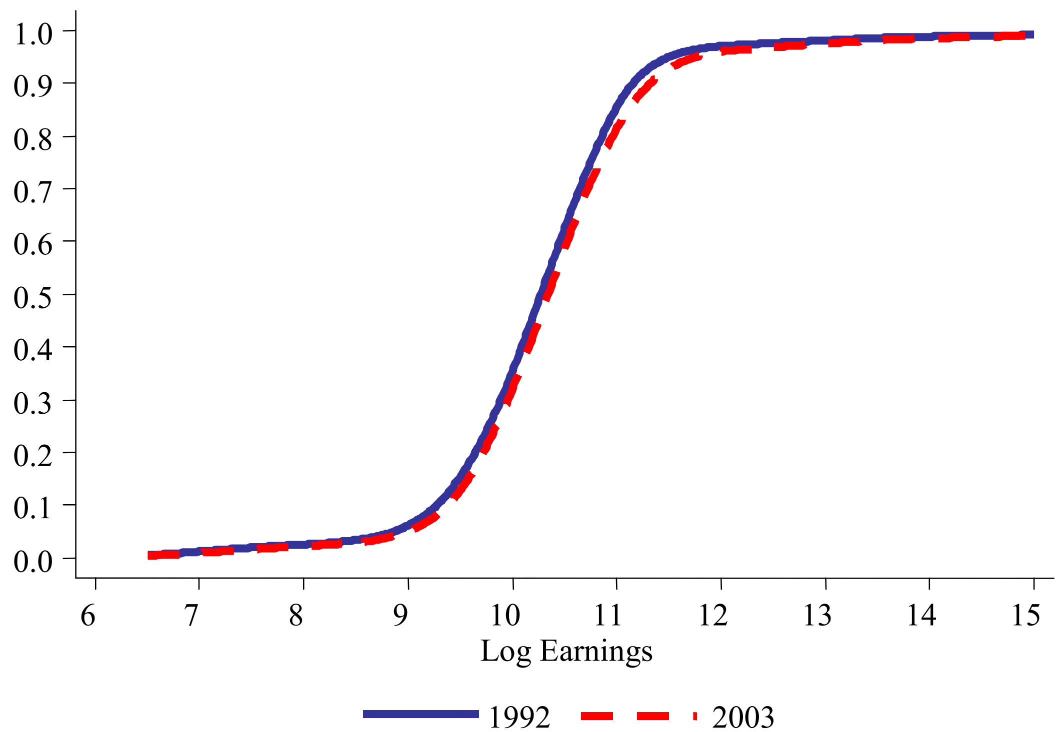
Table 3.1: Earnings Levels, Differences, and Changes by Sector
1992-2003

	2003 Earnings Percentiles			90-10 Log Wage Difference		90-50 Log Wage Difference		50-10 Log Wage Difference	
Sector	90th	50th	10th	2003	Change from 1992	2003	Change from 1992	2003	Change from 1992
Agriculture, Fishing, & Forestry	$44,149	$19,234	$9,126	1.58	-0.14	0.83	-0.02	0.75	-0.12
Mining	$82,705	$45,879	$22,427	1.30	-0.09	0.59	-0.06	0.72	-0.03
Construction	$73,174	$34,181	$14,831	1.60	-0.12	0.76	-0.01	0.83	-0.11
Manufacturing	$90,650	$34,176	$15,183	1.79	0.13	0.98	0.16	0.81	-0.02
Transportation & Communication	$82,987	$39,597	$15,959	1.65	0.13	0.74	0.12	0.91	0.01
Wholesale	$96,084	$34,852	$15,307	1.84	0.11	1.01	0.12	0.82	0.00
Retail	$51,404	$19,820	$8,512	1.80	-0.05	0.95	0.01	0.85	-0.06
Finance, Insurance, & Real Estate	$114,428	$37,083	$16,244	1.95	0.18	1.13	0.15	0.83	0.03
Services	$83,079	$31,346	$11,523	1.98	0.05	0.97	0.08	1.00	-0.03
All Sectors	$82,207	$31,477	$11,992	1.93	0.06	0.96	0.10	0.97	-0.03

Based on LEHD data for CA, IL, MD and NC.

Figure 3.1 depicts empirical estimates of the cumulative distribution functions of annualized earnings for all sectors and, as expected, shows a rightward shift from 1992 to 2003.

Figure 3.1: Log Earnings Cumulative Distributions
1992 and 2003, All Sectors



Based on LEHD data for CA, IL, MD, and NC.

When we repeat the same exercise on an industry-by-industry basis (not shown), we find that although the direction of change is the same for each industry, the most marked rightward shifts were in the agriculture, fishing, and forestry sector and in the finance, insurance, and real estate sector. Other sectors, including manufacturing, transportation and communication, and wholesale, had only modest shifts, but each had a tendency toward increasing inequality (a larger shift right at the top of the distribution). The most remarkable result, however, was the lack of volatility over time in the earnings distributions, which is especially notable given the dramatic changes in the macroeconomic environment that took place over the 1992-2003 period.

The overall rightward shift was not by the same amount at all points of the earnings distribution in each industry, as once again evidenced in Table 3.1. In fact, overall earnings inequality, which from here on we measure by the 90-10 log wage difference, declined in four industries, including agriculture, fishing, and forestry; mining; construction; and retail trade. By contrast, earnings inequality increased in five industries, including manufacturing; transportation and communication; wholesale; finance, insurance, and real estate; and services.

In three of the four industries in which overall inequality declined, much if not all of the decrease was in the lower half of the earnings distribution (as measured by the 50-10 log wage gap). Only in mining was there a notable decline in the upper half of the distribution (the 90-50 log difference). In contrast, lower-tail earnings inequality did not increase in the five industries in which overall inequality increased. The increase in earnings inequality in manufacturing; transportation and communication; wholesale; finance, insurance, and real estate; and services occurred in the upper tail of the earnings distribution. The distance between the 90^{th} and 50^{th} percentiles increased in these six industries, while the 50-10 log difference stayed about the same or decreased slightly. These results corroborate the findings of Autor et al. (2006), who show using CPS data that economy-wide, the 90-50 wage gap grew through the 1990s while the 50-10 difference leveled off after about 1987. However, here we also see differences in trends in upper and lower tail inequality across sectors.

To compare the changes observed in our four-state LEHD data with the U.S. labor market as a whole, we compute estimates of the log real weekly earnings percentiles for 1992 and 2003 for all workers using data from the Monthly Outgoing Rotation Groups of the CPS (CPS-MORG). We provide these estimates in Table 3.2, panel (a). Panel (b) of Table 3.2 presents similar statistics from the CPS-MORG when the samples are limited to the same four states we use in our LEHD analyses. As one can see from the two tables, the estimated change in the 90-10 difference between 1992 and 2003 was somewhat higher for the full-sample CPS-MORG data (0.09) as compared to the LEHD data (0.06). The estimated change in the 90-50 difference for the LEHD data was higher than the CPS-MORG data (0.09 for LEHD versus 0.06 for CPS-MORG). The estimated change in the 50-10 difference, however, was substantially lower for the LEHD data (-0.03 for LEHD versus 0.03 for CPS-MORG). As a comparison of Table 3.1 and panel (b) of Table 3.2 reveals, though, the differences are in large part attributable to the fact that the LEHD data contain only four states.

Table 3.2: Weekly CPS Earnings Differences and Changes by Sector
1992-2003

Sector	90-10 Log Wage Difference		90-50 Log Wage Difference		50-10 Log Wage Difference	
	2003	Change from 1992	2003	Change from 1992	2003	Change from 1992
(a) All States						
Agriculture, Fishing, & Forestry	1.46	0.00	0.79	0.07	0.67	-0.06
Mining	1.34	-0.12	0.66	-0.10	0.68	-0.02
Construction	1.42	0.04	0.73	0.06	0.69	-0.02
Manufacturing	1.51	0.04	0.84	0.07	0.67	0.14
Transportation & Communication	1.57	0.19	0.72	0.13	0.85	0.06
Wholesale	1.59	0.07	0.82	0.01	0.77	0.06
Retail	1.88	0.04	0.91	-0.01	0.97	0.04
Finance, Insurance, & Real Estate	1.75	0.14	0.96	0.12	0.78	0.02
Services	1.97	0.05	0.92	0.04	1.05	0.00
All Sectors	1.86	0.09	0.89	0.06	0.97	0.03
(b) Four States (CA, IL, MD, and NC)						
Agriculture, Fishing, & Forestry	1.46	0.22	0.97	0.24	0.49	-0.02
Mining	1.38	0.04	0.96	0.31	0.43	-0.27
Construction	1.46	-0.02	0.75	0.10	0.71	-0.11
Manufacturing	1.69	0.13	0.97	0.17	0.72	-0.05
Transportation & Communication	1.63	0.36	0.74	0.20	0.89	0.16
Wholesale	1.63	0.13	0.87	0.13	0.76	0.01
Retail	1.89	0.03	0.96	0.02	0.93	0.01
Finance, Insurance, & Real Estate	1.78	0.08	0.95	0.12	0.83	-0.04
Services	2.01	0.04	0.95	0.03	1.06	0.01
All Sectors	1.87	0.05	0.92	0.04	0.95	0.01

Weighted using CPS earnings weights. Based on CPS-MORG data

3.4.2 Changes in Workforce Composition

One possible reason for these changes in the earnings distribution is that workforce characteristics have changed over time. That there is potential for such changes to occur as a result of workforce composition variation is evident from an examination of Table 3.3, which documents patterns of worker mobility in the sample by sector.

Table 3.3: Worker Mobility by Sector
1992-2003

Sector	Number of Worker-Year Pairs in 1992 and 2003	Proportion of Workers in Sector		
		in 1992, not 2003	in 2003, not 1992	in 1992 and 2003
Agriculture, Fishing, & Forestry	578,036	39%	48%	13%
Mining	67,888	56%	29%	14%
Construction	1,511,595	32%	53%	14%
Manufacturing	5,145,894	44%	35%	21%
Transportation & Communication	1,775,581	37%	44%	19%
Wholesale	2,006,918	41%	47%	12%
Retail	4,214,151	39%	49%	12%
Finance, Insurance, & Real Estate	2,101,998	36%	47%	17%
Services	10,196,180	31%	51%	18%

Based on LEHD data for CA, IL, MD and NC.

In manufacturing, for example, of the more than five million workers who were employed in either 1992, 2003, or both years, over 40% were only in the industry in 1992, 35% were only in the industry in 2003, and only 21% were in the industry in both years. As one might expect, churn in the workforce is even more marked in the retail industry, where 39% of workers only appeared in the data in 1992, almost half only appeared in 2003, and fewer than 12% appeared in both years.

Table 3.4 shows that this mobility did not translate into enormous swings in the age, gender, and skill distributions of workers, although there were some dramatic changes in the allocation of workers across sectors. In particular, as services expanded, the mining and manufacturing sectors shrank markedly. In the meantime, both mining and manufacturing, which have historically been predominantly male and skewed toward older workers, remained so in the wake of subtle shifts in industry demographics between 1992 and 2003. Industries such as finance, insurance, and real estate as well as services, which had more females and younger workers at the start of the 1990s, also saw only minor shifts in their overall demographic profiles over the sample period. Although the skill level of the workforce increased in all industries between 1992 and 2003 (using both the overall measure of human capital, which includes experience, and the individual fixed effect, which does not), the swings were not substantial.

Table 3.4: Changes in Workforce Composition by Sector
1992-2003

Sector	Employment in 1992	Change Between 1992 and 2003 in: Employment	Proportion of Workforce: Male	14-29	30-49	50+	Human Capital (log points)	Individual Fixed Effects (log points)
Agriculture, Fishing, & Forestry	300,709	17%	-7%	-6%	1%	5%	0.17	0.05
Mining	48,063	-39%	2%	0%	-11%	10%	0.11	0.08
Construction	704,268	46%	-1%	-5%	1%	4%	0.10	0.03
Manufacturing	3,357,441	-14%	2%	-7%	-1%	7%	0.17	0.06
Transportation & Communication	991,212	14%	2%	-3%	-4%	7%	0.09	0.06
Wholesale	1,066,376	11%	0%	-7%	0%	7%	0.13	0.06
Retail	2,138,239	20%	0%	-5%	1%	4%	0.12	0.04
Finance, Insurance, & Real Estate	1,111,889	21%	3%	-5%	-1%	6%	0.14	0.05
Services	4,998,570	41%	0%	-4%	-4%	7%	0.08	0.06

Based on LEHD data for CA, IL, MD and NC.

3.4.3 Changes in Firm Characteristics

Another possible reason for changes in earnings inequality is changes in the types of firms that are hiring workers. We examine this possibility in Table 3.5, which can be read in the same way as Table 3.3. In manufacturing, for example, of the more than 100,000 unique firms that employed individuals in either 1992, 2003, or both years, 36% were only in the industry in 1992, 37% were only in the industry in 2003, and only 27% were there in both years. The rates are even lower in industries with more small firms; in retail trade, for example, 40% were only in the industry in 1992, 41% were only in the industry in 2003, and about 20% were in the industry in both years. While industry differences exist, all industries had high rates of firm entry and exit over the 1992-2003 period.

Table 3.5: Firm Entry and Exit Rates by Sector
1992-2003

Sector	Number of Firm-Year Pairs in 1992 and 2003	Entrants		Exiters		Continuers	
		Proportion	Mean firm fixed effect*	Proportion	Mean firm fixed effect*	Proportion	Mean firm fixed effect*
Agriculture, Fishing, & Forestry	50,825	32%	-0.28	39%	-0.23	29%	-0.23
Mining	2,135	45%	0.38	35%	0.28	20%	0.35
Construction	155,195	33%	0.02	45%	0.05	22%	0.10
Manufacturing	107,200	36%	0.20	37%	0.15	27%	0.18
Transportation & Communication	56,355	35%	0.18	45%	0.16	20%	0.21
Wholesale	143,414	36%	0.11	43%	0.12	21%	0.11
Retail	263,093	40%	-0.23	41%	-0.24	20%	-0.22
Finance, Insurance, & Real Estate	120,763	33%	0.13	46%	0.20	22%	0.13
Services	686,606	31%	0.05	49%	0.04	19%	0.01

* Means are employment weighted.
Based on LEHD data for CA, IL, MD and NC.

3.4.4 Changes in Assortative Matching

Changes in the joint distribution of employee human capital and firm pay levels over time constitute another possible source of change in earnings distributions. Suppose we estimate a linear panel data model with fixed firm and individual effects such as that described in Abowd et al. (1999),

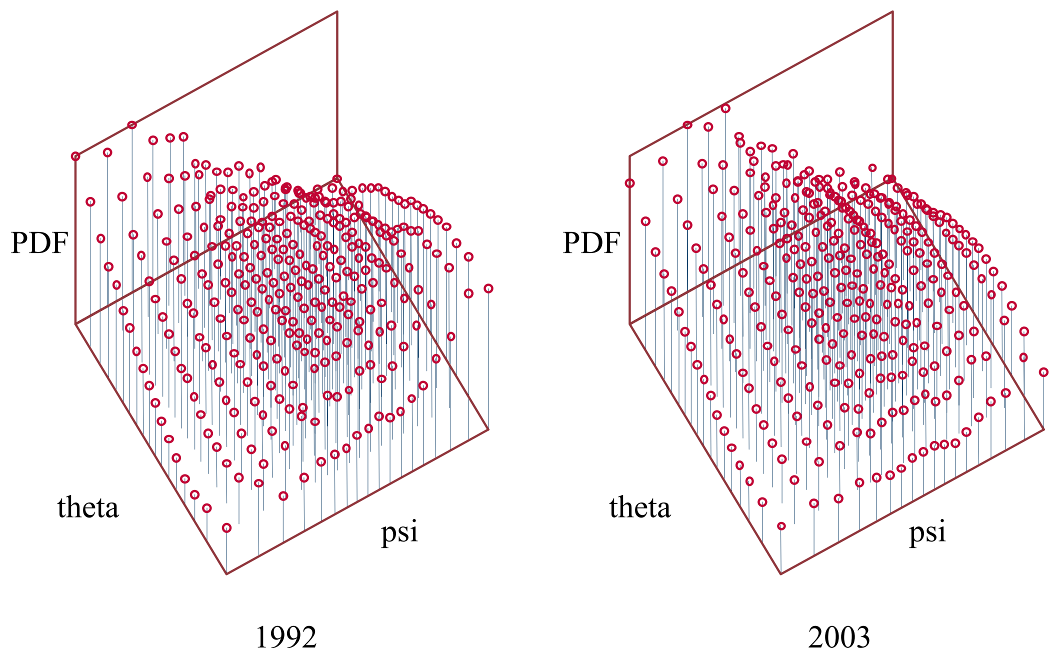
$$y_{it} = \mathbf{x_{it}\beta} + \theta_i + \psi_{j(i,t)} + \varepsilon_{it}$$

where y_{it} are individual *i*'s earnings at time *t*, $\mathbf{x_{it}}$ is a vector of observed productivity measures of individual *i* at time *t*, θ_i is an individual fixed effect that measures an individual's unobserved productivity or human capital and $\psi_{j(i,t)}$ the fixed effect of the firm that individual *i* works for at time *t* and measures a firm's pay policy. Then changes in the distribution of earnings may be due to changes in the joint distribution of θ and ψ. For example, over time it may be the case that high θ individuals are more likely to work at high ψ firms and low θ individuals are more likely to work at low ψ firms, which would tend to increase earnings inequality.

Using the estimated values of θ and ψ from this model, Figure 3.2 plots the joint distributions of θ and ψ for 1992 and 2003.[87]

[87] The estimates include age variables as controls.

Figure 3.2: Joint Distribution of Worker Human Capital (theta) and Firm Pay Policy (psi) Match
1992 and 2003, All Sectors

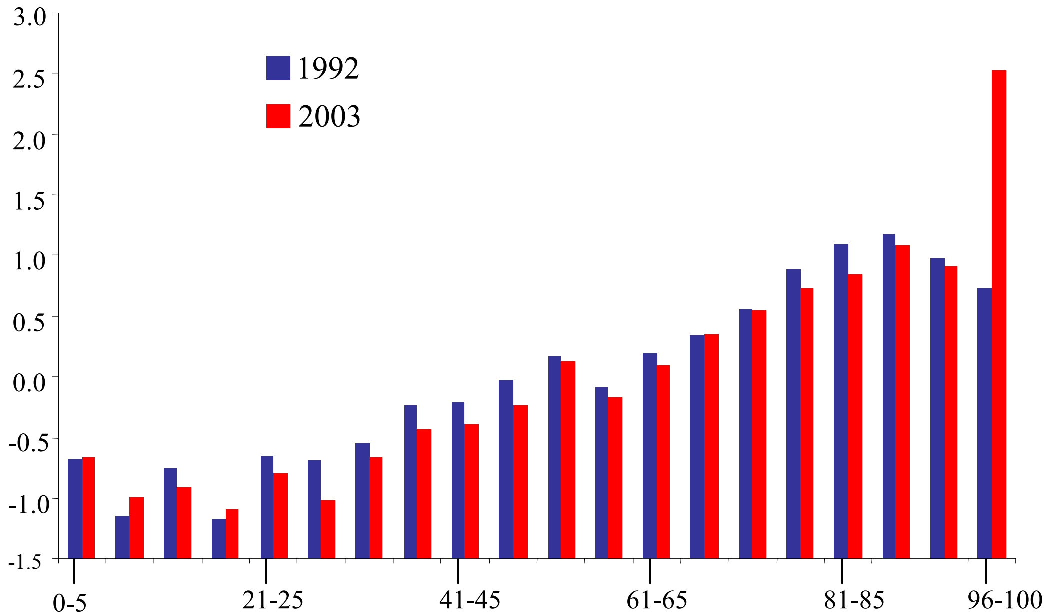


Based on LEHD data for CA, IL, MD, and NC.

As Figure 3.2 reveals, between 1992 and 2003, the likelihood of a low θ individual being attached to a high ψ firm declined. That is, individuals with low skill levels were less likely in 2003 than 1992 to be paired with firms with high pay policies, which could be construed as evidence of increasing positive assortative matching.

Figure 3.3 displays the expected values of θ by quantile groups of ψ for 1992 and 2003. This figure clearly shows that there has been a large upward shift between 1992 and 2003 in the expected value of θ for the highest ψ group of firms. Based solely upon Figure 3.3, however, we cannot determine whether this shift is a result of entry and exit of different types of firms and workers or is due to a reshuffling of worker-firm matches.

Figure 3.3: Expected Value of Worker Human Capital (theta) by Percentile of Firm Pay Policy (psi)
1992 and 2003, All Sectors



Based on LEHD data for CA, IL, MD, and NC.
Percentiles of theta and psi are measured as deviations from year means.

Indeed, although these descriptive statistics hint at the potential for worker and job reallocation to affect earnings inequality, they report average effects for all firms and workers in the industry. To investigate the trends in inequality further, in the next section we develop an econometric approach to examine different points of the earnings distribution.

3.5 Decomposition Methodology

In this section, we develop econometric methods for decomposing changes in earnings distributions using employer-employee matched panel data. For ease of exposition in describing the earnings decomposition methodology, we initially assume that we have only one continuous exogenous predictor variable, x. Let θ be a variable representing an individual's (unobserved) productivity, which is assumed to be constant over time. Further, let ψ represent a firm's (unobserved) pay policy variable, which is also assumed to be constant over time. We furthermore assume that an individual's earnings are determined by the function $y = g(\varepsilon, \theta, \psi, x)$, where ε is a random error component that is independent of x, θ, and ψ.

Again for expositional simplicity, we assume that the variables x, θ, ψ, and ε have a continuous joint probability density function f_t for each time period, t = 1, 2.

$$\text{(1)} \qquad \mathrm{d}P_t(\varepsilon, \theta, \psi, x) = f_t(\varepsilon, \theta, \psi, x)\mathrm{dt}$$

One important facet of the data is the fact that between the two time periods, within an industry firms can be created or destroyed and workers may enter or exit. Thus, for both firms and workers, there are stayers (*s*), leavers (*l*), and new entrants (*n*). Therefore, we can rewrite the joint distribution in (1) at time 1 as a mixture of these worker-firm types,

$$\text{(2)} \qquad \begin{aligned} f_1(\varepsilon, \theta, \psi, x) &= p_1(\mathrm{w}{=}s,\ \mathrm{f}{=}s) f_1^{ss}(\varepsilon, \theta, \psi, x) + p_1(\mathrm{w}{=}l,\ \mathrm{f}{=}s) f_1^{ls}(\varepsilon, \theta, \psi, x) + \\ & p_1(\mathrm{w}{=}s,\ \mathrm{f}{=}l) f_1^{sl}(\varepsilon, \theta, \psi, x) + p_1(\mathrm{w}{=}l,\ \mathrm{f}{=}l) f_1^{ll}(\varepsilon, \theta, \psi, x) \end{aligned}$$

where p_1(w=*s,* f=*s)* is the fraction of worker-firm matches where both firm and worker remain in the industry until time 2, p_1(w=*l*, f=s) is the fraction of worker-firm matches where the firm remains in the industry until time 2 but the worker leaves, p_1(w=*s*, f=*l*) is the fraction of worker-firm matches where the worker remains in the industry until time 2 but the firm leaves, and p_1(w=*l*, f=*l*) is the fraction of worker-firm matches where both the worker and firm leave by time 2. The distributions $f_1^{ss}(\varepsilon,\theta,\psi,x)$, $f_1^{ls}(\varepsilon,\theta,\psi,x)$, $f_1^{sl}(\varepsilon,\theta,\psi,x)$, and $f_1^{ll}(\varepsilon,\theta,\psi,x)$ are the analogous conditional distributions. On the other hand, the joint distribution in (1) at time 2 as can be written as

$$\begin{aligned} f_2(\varepsilon,\theta,\psi,x) &= p_2(\text{w}=s,\ \text{f}=s) f_2^{ss}(\varepsilon,\theta,\psi,x) + p_2(\text{w}=n,\ \text{f}=s) f_2^{ns}(\varepsilon,\theta,\psi,x) + \\ &\quad p_2(\text{w}=s,\ \text{f}=n) f_2^{sn}(\varepsilon,\theta,\psi,x) + p_2(\text{w}=n,\ \text{f}=n) f_2^{nn}(\varepsilon,\theta,\psi,x) \end{aligned} \tag{3}$$

where n indicates new entrants into the industry between time 1 and time 2.

The order of the sequential decomposition may differ. Here, we first analyze the extent to which worker entry and exit has changed the earnings distribution by considering the counterfactual earnings distribution that would have arisen had there been no exit and entry of workers. In that situation, (3) becomes

$$f_2^{w}(\varepsilon,\theta,\psi,x) = \frac{p_2(\text{w}=s,\ \text{f}=s) f_2^{ss}(\varepsilon,\theta,\psi,x) + p_1(\text{w}=l,\ \text{f}=s) f_1^{ls}(\varepsilon,\theta,\psi,x) + p_2(\text{w}=s,\ \text{f}=n) f_2^{sn}(\varepsilon,\theta,\psi,x)}{R} \tag{4}$$

where $R = p_2(\text{w}=s,\ \text{f}=s) + p_1(\text{w}=l,\ \text{f}=s) + p_2(\text{w}=s,\ \text{f}=n)$. In this case, we have assumed that, had those individuals who left the sector actually stayed, they would have matched with firms in a manner analogous to the distribution of workers who actually left those firms that stayed in the industry. Next, we consider the impact of the change in the distribution of x. Here, we note that, for example, $f_2^{ss}(\varepsilon,\theta,\psi,x) \equiv f_2^{ss}(\varepsilon,\theta,\psi \mid x) f_2(x)$, and replace $f_2(x)$ by $f_1(x)$. This yields the following expression:

(5) $$f_2^{ss,x}(\varepsilon,\theta,\psi,x) \equiv f_2^{ss}(\varepsilon,\theta,\psi \mid x) f_1(x) = f_2^{ss}(\varepsilon,\theta,\psi,x)\left(f_1(x) \big/ f_2(x) \right)$$

The other terms in (4) are modified in a similar fashion. Thus, we have the following:

(6) $$f_2^{w,x}(\varepsilon,\theta,\psi,x) = \frac{p_2(\text{w}=s,\ \text{f}=s) f_2^{ss,x}(\varepsilon,\theta,\psi,x) + p_1(\text{w}=l,\ \text{f}=s) f_1^{ls,x}(\varepsilon,\theta,\psi,x) + p_2(\text{w}=s,\ \text{f}=n) f_2^{sn,x}(\varepsilon,\theta,\psi,x)}{R}$$

Next, we evaluate the impact of firm entry and exit by considering the counterfactual that assumes that the set of firms (as well as workers and x) at time 2 is the same as in time 1:

(7) $$f_2^{w,x,e}(\varepsilon,\theta,\psi,x) = \frac{p_1(\text{w}=s,\ \text{f}=s) f_2^{ss,x}(\varepsilon,\theta,\psi,x) + p_1(\text{w}=l,\ \text{f}=s) f_1^{ls,x}(\varepsilon,\theta,\psi,x) + p_1(\text{w}=l,\ \text{f}=l) f_1^{ll,x}(\varepsilon,\theta,\psi,x)}{\check{R}}$$

Finally, after we have restricted the set of firms and workers to be the same as in time 1, it is still possible to examine how the distribution of θ given ψ may have changed between periods 1 and 2 due to a reallocation of workers across firms within the sector. Now,

(8) $$\begin{aligned} & f_2^{w,x,e}(\varepsilon,\theta,\psi,x) \equiv f_2^{w,x,e}(\varepsilon,\theta,\psi,x \mid \theta,\psi) f_2^{w,x,e}(\theta,\psi) \\ & = f_2^{w,x,e}(\varepsilon,\theta,\psi,x \mid \theta,\psi) f_2^{w,x,e}(\theta \mid \psi) f_1(\psi) \end{aligned}$$

so we can define

(9) $$f_2^{w,x,e,a}(\varepsilon,\theta,\psi,x) \equiv f_2^{w,x,e}(\varepsilon,\theta,\psi,x \mid \theta,\psi) f_1^{w,x,e}(\theta \mid \psi) f_1(\psi)$$

where the superscript refers to the fact that we are now holding the allocation of workers to firms constant.

Based on these counterfactual distributions, we can decompose changes in the total earnings distribution. Let Y be the range of y and let A be a subset of Y (i.e., $A \subset Y$). Then we can write

(10) $$P_t(y \in A) = \int_{\{\varepsilon,\theta,\psi,x\}:g(\varepsilon,\theta,\psi,x)\in A} f_t(\varepsilon,\theta,\psi,x)\,d\varepsilon\,d\theta\,d\psi\,dx$$

We can therefore define the counterfactual probabilities by

(11) $$P_2^{w}(y \in A) = \int_{\{\varepsilon,\theta,\psi,x\}:g(\varepsilon,\theta,\psi,x)\in A} f_2^{w}(\varepsilon,\theta,\psi,x)\,d\varepsilon\,d\theta\,d\psi\,dx$$

(12) $$P_2^{w,x}(y \in A) = \int_{\{\varepsilon,\theta,\psi,x\}:g(\varepsilon,\theta,\psi,x)\in A} f_2^{w,x}(\varepsilon,\theta,\psi,x)\,d\varepsilon\,d\theta\,d\psi\,dx$$

(13) $$P_2^{w,x,e}(y \in A) = \int_{\{\varepsilon,\theta,\psi,x\}:g(\varepsilon,\theta,\psi,x)\in A} f_2^{w,x,e}(\varepsilon,\theta,\psi,x)\,d\varepsilon\,d\theta\,d\psi\,dx$$

(14) $$P_2^{w,x,e,a}(y \in A) = \int_{\{\varepsilon,\theta,\psi,x\}:g(\varepsilon,\theta,\psi,x)\in A} f_2^{w,x,e,a}(\varepsilon,\theta,\psi,x)\,d\varepsilon\,d\theta\,d\psi\,dx$$

The "Oaxaca type" decomposition of the change in the probability of the event $y \in A$ can then be written as

$$(15)\qquad \begin{aligned} &P_2(y\in A)-P_1(y\in A)=\\ &(P_2(y\in A)-P_2^{w}(y\in A))+(P_2^{w}(y\in A)-P_2^{w,x}(y\in A))\\ &+(P_2^{w,x}(y\in A)-P_2^{w,x,e}(y\in A))+(P_2^{w,x,e}(y\in A)-P_2^{w,x,e,a}(y\in A))\\ &+(P_2^{w,x,e,a}(y\in A)-P_2(y\in A)) \end{aligned}$$

Suppose, in general, that we wish to decompose the expected value of some function *r* of earnings, *E(r(y))*. In that case, we would have the following:

$$\begin{aligned} &E_2(r(y))-E_1(r(y))=\\ &\int_{\{\varepsilon,\theta,\psi,x\}\in D} r(g(\varepsilon,\theta,\psi,x))f_2(\varepsilon,\theta,\psi,x)d\varepsilon d\theta d\psi dx-\int_{\{\varepsilon,\theta,\psi,x\}\in D} r(g(\varepsilon,\theta,\psi,x))f_1(\varepsilon,\theta,\psi,x)d\varepsilon d\theta d\psi dx=\\ &\left(\int_{\{\varepsilon,\theta,\psi,x\}\in D} r(g(\varepsilon,\theta,\psi,x))f_2(\varepsilon,\theta,\psi,x)d\varepsilon d\theta d\psi dx-\int_{\{\varepsilon,\theta,\psi,x\}\in D} r(g(\varepsilon,\theta,\psi,x))f_2^{w}(\varepsilon,\theta,\psi,x)d\varepsilon d\theta d\psi dx\right)+\\ &\left(\int_{\{\varepsilon,\theta,\psi,x\}\in D} r(g(\varepsilon,\theta,\psi,x))f_2^{w}(\varepsilon,\theta,\psi,x)d\varepsilon d\theta d\psi dx-\int_{\{\varepsilon,\theta,\psi,x\}\in D} r(g(\varepsilon,\theta,\psi,x))f_2^{w,x}(\varepsilon,\theta,\psi,x)d\varepsilon d\theta d\psi dx\right)+\\ &\left(\int_{\{\varepsilon,\theta,\psi,x\}\in D} r(g(\varepsilon,\theta,\psi,x))f_2^{w,x}(\varepsilon,\theta,\psi,x)d\varepsilon d\theta d\psi dx-\int_{\{\varepsilon,\theta,\psi,x\}\in D} r(g(\varepsilon,\theta,\psi,x))f_2^{w,x,e}(\varepsilon,\theta,\psi,x)d\varepsilon d\theta d\psi dx\right)+\\ &\left(\int_{\{\varepsilon,\theta,\psi,x\}\in D} r(g(\varepsilon,\theta,\psi,s))f_2^{w,x,e}(\varepsilon,\theta,\psi,x)d\varepsilon d\theta d\psi dx-\int_{\{\varepsilon,\theta,\psi,x\}\in D} r(g(\varepsilon,\theta,\psi,x))f_2^{w,x,e,a}(\varepsilon,\theta,\psi,x)d\varepsilon d\theta d\psi dx\right)+\\ &\left(\int_{\{\varepsilon,\theta,\psi,x\}\in D} r(g(\varepsilon,\theta,\psi,s))f_2^{w,x,e,a}(\varepsilon,\theta,\psi,x)d\varepsilon d\theta d\psi dx-\int_{\{\varepsilon,\theta,\psi,x\}\in D} r(g(\varepsilon,\theta,\psi,x))f_1(\varepsilon,\theta,\psi,x)d\varepsilon d\theta d\psi dx\right) \end{aligned}$$

where *D* denotes the domain of ($\varepsilon,\theta,\psi,x$). Note that in (15), we have $r(y)=I(y\in A)$, where *I* is the indicator function.[88]

[88] This decomposition technique can be extended to the case in which the earnings function $y=g(\varepsilon,\theta,\psi,x)$ varies over time (i.e., $y=g_t(\varepsilon,\theta,\psi,x)$) by incorporating an additional decomposition step that would measure the impact of this "structural" change on the distribution of earnings.

We apply this general decomposition technique to the LEHD data in order to explore the determinants of earnings distribution changes over time for different industries. To put more structure on the relationship between y and $(\varepsilon, \theta, \psi, x)$, we assume that the relationship takes the form of a linear panel data model with fixed firm and individual effects (Abowd et al. 1999). The function g in this case has the following form:[89]

$$(16) \qquad y_{it} = g(\varepsilon, \theta, \psi, \mathbf{x}) = \mathbf{x_{it}\beta} + \theta_i + \psi_{j(i,t)} + \varepsilon_{it}$$

We use (16) to estimate the determinants of log earnings using the entire LEHD database. Since our focus is on examining changes in earnings distributions over time within industries, from this estimation we calculate $dP_t(\varepsilon, \theta, \psi, \mathbf{x})$ for each industry.

In the LEHD data, all exogenous variables (e.g., age and gender) are discrete. Thus, the discussion presented above, which analyzed decompositions with a continuous explanatory variable, does not directly apply. With discrete explanatory variables, however, we simply estimate the distribution of $(\varepsilon, \theta, \psi)$ for each distinct category of every exogenous variable within each industry-time cell.

To perform the full decomposition, we must estimate the continuous distribution of $(\varepsilon, \theta, \psi)$ for several categories of $\mathbf{x}$ within each of the nine industries. Since the number of observations in the LEHD data is extremely large, we accomplished this task by discretizing these variables. We discretized each variable by breaking the range into 100 mutually exclusive intervals and assigning the midpoint value to each observation

[89] We assume that no structural change has occurred over the relevant time period.

that falls within the interval. We applied this method for all intervals except the lowest and highest intervals (which are unbounded). For the highest (lowest) interval, we assign a value that equals the average of the lower (higher) boundary value and the highest (lowest) observed value in the (industry) sample. We denote the discretized values by ($\varepsilon^d, \theta^d, \psi^d$) and recompute earnings by

$$(17) \qquad y_{it}^d = \mathbf{x_{it}}\boldsymbol{\beta} + \theta_i^d + \psi_{j(i,t)}^d + \varepsilon_{it}^d .$$

We then perform the decompositions on y_{it}^d using the discrete analogs of the equations above.

3.6 Decomposition Results

In our initial decomposition, we break out the change in the earnings distribution for all sectors into the amount attributable to changes in the distribution of employment across industries, worker entry and exit, changes in observable worker characteristics, firm entry and exit, and changes in the distribution of unobserved worker attributes (θ) for a given firm pay policy (ψ) (i.e., sorting). The results of this decomposition appear in Table 3.6.[90] The results in the first three rows of each panel decompose the sources of earnings changes at the 90th, 50th, and 10th percentiles of the earnings distribution, while the last three rows describe the effect on changes in inequality. Thus, the first column indicates that log earnings in 2003 stood at 9.38 for a worker in the 10th percentile, 10.34 for a worker in the 50th percentile, and 11.32 for a worker in the 90th percentile. As a

[90] While the order of the decomposition may affect the results, switching the order of worker entry and exit and firm entry and exit in the decompositions led to similar findings. For the sake of brevity, these results are not reported.

result, the 90th percentile worker made roughly 194% more than the 10th percentile worker and 98% more than the median worker. The median worker, meanwhile, earned about 96% more than the 10th percentile worker. A comparison of this with the 1992 distribution, which we present in the second to last column, shows that inequality as measured by the 90/10 ratio was lower in 1992 relative to 2003; the 90th percentile worker made 188% as much as the 10th percentile worker in 1992. The increase in inequality between 1992 and 2003 came about entirely from higher earnings for the 90th percentile worker relative to the median worker; in fact, the rise in the 90-50 difference was so large as to overwhelm an actual decline in the 50-10 difference.

These gross changes, however, mask considerable flux in the earnings distribution that can be attributed to changes in the underlying factors, which we break out in the intervening columns of Table 3.6. The columns report the values of each earnings percentile and difference taking out each component of the decomposition sequentially, with panel (a) showing overall levels and panel (b) showing marginal contributions of each factor. For example, column (2) shows that the 90-10 difference in 2003 would have been 1.93 instead of 1.94 (a marginal contribution of 0.01) if we control for changes in the distribution of workers across different major sectors of the economy; column (6), meanwhile, reveals that if we account for changes in the sector distribution, worker entry and exit, changes in observable worker characteristics, firm entry and exit, and worker-firm sorting, the 90-10 difference would have been 2.16 (with sorting having a marginal contribution of 0.88).

Table 3.6: Decomposition of the Change in the Earnings Distribution, All Sectors
1992-2003

Measure	(1) 2003	(2) Sector Distribution	(3) + Worker Entry and Exit	(4) + Change in Observable Worker Characteristics	(5) + Firm Entry and Exit	(6) + Sorting of Firms and Workers	(7) 1992	(8) Change from 1992 to 2003
(a) Levels								
10th percentile	9.38	9.39	9.40	9.25	8.26	9.08	9.28	0.10
50th percentile	10.34	10.35	10.36	10.21	10.06	10.19	10.27	0.07
90th percentile	11.32	11.32	11.34	11.25	11.30	11.24	11.16	0.17
90-10 difference	1.94	1.93	1.93	2.01	3.04	2.16	1.88	0.06
90-50 difference	0.98	0.98	0.98	1.05	1.24	1.05	0.88	0.10
50-10 difference	0.96	0.95	0.95	0.96	1.80	1.11	1.00	-0.03
(b) Marginal Effects								
10th percentile	9.38	-0.01	-0.01	0.16	0.98	-0.82	9.28	0.10
50th percentile	10.34	-0.01	-0.01	0.15	0.15	-0.13	10.27	0.07
90th percentile	11.32	0.00	-0.02	0.08	-0.04	0.06	11.16	0.17
90-10 difference	1.94	0.01	0.00	-0.08	-1.03	0.88	1.88	0.06
90-50 difference	0.98	0.01	-0.01	-0.06	-0.20	0.19	0.88	0.10
50-10 difference	0.96	0.01	0.00	-0.01	-0.83	0.69	1.00	-0.03

Based on LEHD data for CA, IL, MD, and NC.

An examination of the column (2) of Table 3.6 reveals that changes in the distribution of employment across sectors led to small increases in both the 90-50 and 50-10 log earnings differences between 1992 and 2003. This suggests that workers have been moving into industries with greater inequality from industries with less inequality, though such cross-sector reallocation alone has not been sufficiently large to give rise to large changes in overall observed inequality. Worker entry and exit, meanwhile, had almost no impact on the 50-10 log earnings difference or the 90-50 log earnings difference. Changes in observed worker characteristics had more sizable effects, leading in particular to a marked decline in the 90-50 log earnings difference.

While the entry and exit of firms led to large decreases in the 50-10 and 90-50 log earnings differences, the effect was almost entirely offset by the impact of sorting of workers and firms. The effects of these final two factors were particularly evident at the lower end of the earnings distribution. Looking at the first row, the results reveal that had there been no entry and exit of firms (controlling for changes in the sector distribution, worker entry and exit, and changes in observable worker characteristics), earnings at the 10^{th} percentile would have been substantially lower; indeed, firm turnover acted to buttress earnings at the bottom end of the distribution disproportionately. However, conditional on firm entry and exit and other underlying factors, the sorting of firms and workers acted to depress earnings levels at the bottom end of the distribution and bolster earnings levels at the at the top end; ultimately, then, earnings inequality would have been much lower had it not been for the contribution of assortative matching over the 1992-2003 period.

The results in Table 3.6 highlight the relative importance of firm entry and exit as well as worker sorting in driving changes in earnings distributions across industries over time. The findings are broadly consistent with a model of creative destruction in which assortative matching among workers and firms occurs alongside firm turnover that ushers in new, more productive businesses to supplant those that are failing (Jovanovic 1982, Haltiwanger et al. 2007).

Table 3.7 presents the same set of sequential decompositions of the cumulative distribution functions by sector, but now showing only the marginal contributions of each factor for brevity. Panel (a) presents results for industries in which inequality (as measured again by the 90-10 log wage difference) declined, and panel (b) presents results for industries in which inequality increased. The first striking result of the decompositions is the degree to which each separate factor affected the earnings distributions, even in industries such as services where in net terms there were not substantial changes in earnings over time. Indeed, our analysis reveals remarkable differences in the way in which changes in the composition of workers, firms, and the match between the two affects earnings in different parts of the distribution, often in offsetting ways.

Table 3.7: Decompositions of Changes in Earnings Distributions by Sector
1992-2003

(a) Sectors with Declining Inequality

Measure	(1) 2003	(2) + Worker Entry and Exit	(3) + Change in Observable Worker Characteristics	(4) + Firm Entry and Exit	(5) + Sorting of Firms and Workers	(6) 1992	(7) Change from 1992 to 2003
Agriculture, Forestry & Fisheries							
10th percentile	9.12	-0.01	0.21	0.26	-0.20	8.84	0.28
50th percentile	9.86	-0.01	0.14	0.04	-0.02	9.70	0.16
90th percentile	10.70	-0.01	0.12	-0.11	0.10	10.56	0.14
90-10 difference	1.58	0.00	-0.08	-0.37	0.29	1.72	-0.14
90-50 difference	0.83	-0.01	-0.02	-0.15	0.12	0.85	-0.02
50-10 difference	0.75	0.00	-0.07	-0.23	0.18	0.87	-0.12
Mining							
10th percentile	10.02	0.01	0.22	1.34	-1.37	9.99	0.03
50th percentile	10.73	0.01	0.11	0.29	-0.36	10.74	-0.01
90th percentile	11.32	0.01	-0.03	0.13	-0.03	11.39	-0.07
90-10 difference	1.31	-0.01	-0.25	-1.21	1.35	1.40	-0.09
90-50 difference	0.59	0.00	-0.14	-0.17	0.33	0.65	-0.06
50-10 difference	0.72	0.00	-0.12	-1.04	1.01	0.75	-0.03

Table 3.7 (continued): Decompositions of Changes in Earnings Distributions by Sector
1992-2003

(a) Sectors with Declining Inequality

Measure	(1) 2003	(2) + Worker Entry and Exit	(3) + Change in Observable Worker Characteristics	(4) + Firm Entry and Exit	(5) + Sorting of Firms and Workers	(6) 1992	(7) Change from 1992 to 2003
Construction							
10th percentile	9.61	-0.01	0.16	0.56	-0.36	9.41	0.20
50th percentile	10.44	-0.02	0.12	0.16	-0.08	10.35	0.09
90th percentile	11.20	-0.02	0.07	0.03	0.01	11.13	0.08
90-10 difference	1.60	-0.01	-0.09	-0.53	0.37	1.72	-0.12
90-50 difference	0.76	0.00	-0.06	-0.12	0.09	0.77	-0.01
50-10 difference	0.84	-0.01	-0.04	-0.41	0.28	0.94	-0.11
Retail							
10th percentile	9.05	-0.01	0.11	0.48	-0.36	8.93	0.12
50th percentile	9.89	-0.01	0.14	0.13	-0.06	9.83	0.06
90th percentile	10.85	-0.01	0.12	-0.02	0.07	10.78	0.07
90-10 difference	1.80	-0.01	0.01	-0.50	0.43	1.85	-0.05
90-50 difference	0.95	0.00	-0.02	-0.15	0.13	0.94	0.01
50-10 difference	0.85	0.00	0.03	-0.35	0.30	0.90	-0.06

Table 3.7 (continued): Decompositions of Changes in Earnings Distributions by Sector 1992-2003

(b) Sectors with Rising Inequality							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Measure	2003	+ Worker Entry and Exit	+ Change in Observable Worker Characteristics	+ Firm Entry and Exit	+ Sorting of Firms and Workers	1992	Change from 1992 to 2003
Manufacturing							
10th percentile	9.63	0.01	0.20	1.35	-1.29	9.55	0.08
50th percentile	10.44	0.01	0.21	0.13	-0.25	10.38	0.06
90th percentile	11.42	0.00	0.13	-0.08	-0.01	11.20	0.22
90-10 difference	1.79	0.00	-0.07	-1.43	1.28	1.65	0.14
90-50 difference	0.98	0.00	-0.08	-0.21	0.24	0.82	0.16
50-10 difference	0.81	0.00	0.01	-1.22	1.05	0.83	-0.02
Transportation & Communication							
10th percentile	9.68	-0.01	0.17	0.70	-0.69	9.70	-0.02
50th percentile	10.59	-0.01	0.09	0.13	-0.17	10.61	-0.02
90th percentile	11.33	-0.01	0.07	0.01	-0.05	11.22	0.11
90-10 difference	1.65	0.01	-0.11	-0.69	0.65	1.52	0.13
90-50 difference	0.74	0.01	-0.03	-0.12	0.13	0.62	0.13
50-10 difference	0.91	0.00	-0.08	-0.57	0.52	0.90	0.01

Table 3.7 (continued): Decompositions of Changes in Earnings Distributions by Sector 1992-2003

(b) Sectors with Rising Inequality

Measure	(1) 2003	(2) + Worker Entry and Exit	(3) + Change in Observable Worker Characteristics	(4) + Firm Entry and Exit	(5) + Sorting of Firms and Workers	(6) 1992	(7) Change from 1992 to 2003
Wholesale Trade							
10th percentile	9.64	0.00	0.17	0.46	-0.38	9.55	0.09
50th percentile	10.46	0.00	0.15	0.02	-0.09	10.38	0.08
90th percentile	11.47	0.00	0.08	-0.38	0.29	11.28	0.20
90-10 difference	1.84	0.00	-0.10	-0.84	0.67	1.73	0.11
90-50 difference	1.01	0.00	-0.07	-0.40	0.38	0.90	0.12
50-10 difference	0.82	0.00	-0.03	-0.44	0.29	0.83	0.00
Finance, Insurance, & Real Estate							
10th percentile	9.70	-0.01	0.18	0.79	-0.66	9.53	0.17
50th percentile	10.52	-0.01	0.16	0.14	-0.08	10.32	0.20
90th percentile	11.65	-0.01	0.09	-0.10	0.20	11.30	0.35
90-10 difference	1.95	0.00	-0.09	-0.89	0.86	1.77	0.18
90-50 difference	1.13	0.00	-0.07	-0.24	0.28	0.97	0.15
50-10 difference	0.83	0.00	-0.02	-0.65	0.58	0.80	0.03

Table 3.7 (continued): Decompositions of Changes in Earnings Distributions by Sector 1992-2003

(b) Sectors with Rising Inequality							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Measure	2003	+ Worker Entry and Exit	+ Change in Observable Worker Characteristics	+ Firm Entry and Exit	+ Sorting of Firms and Workers	1992	Change from 1992 to 2003
Services							
10th percentile	9.35	0.02	0.13	1.27	-0.99	9.24	0.11
50th percentile	10.35	0.02	0.11	0.19	-0.08	10.27	0.08
90th percentile	11.33	0.01	0.04	0.00	0.11	11.16	0.17
90-10 difference	1.98	-0.01	-0.09	-1.26	1.10	1.92	0.05
90-50 difference	0.98	-0.01	-0.07	-0.18	0.18	0.89	0.08
50-10 difference	1.00	0.00	-0.03	-1.08	0.92	1.03	-0.03

Entries in columns (2) - (5) report the change in the measure when the factor is either assumed not to have occurred (as with worker and firm entry and exit) or replaced by its 1992 value (as with observed worker characteristics and the conditional distribution of worker matches given a firm level of pay).
Based on LEHD data for CA, IL, MD, and NC.

Considering first the four industries in which overall inequality declined, column (2) of panel (a) reveals that, despite the high levels of worker churning, the churning was among workers of the same average skill level (θ), resulting in very little change in inequality in each of the sectors. That this is true in every industry suggests that, by and large, workforce quality within each industry is quite persistent, which is consistent with work by Haltiwanger et al. (2007). An analysis of column (3) shows that, holding θ constant, the aging of the workforce (and the associated returns to experience) acted to decrease earnings inequality in three of the four industries, with little impact in the retail sector. Increased experience led to increased earnings at both ends of the distribution, but with a larger impact at the 10^{th} percentile than at the 90^{th} (except in retail), thus decreasing inequality.

The entry and exit of firms clearly has an enormous impact on the earnings distribution, as is evident from a comparison of column (3) with column (4) in panel (a) of Table 3.7. In mining, column (4) (compared to column (3)) indicates that if no firm entry or exit had occurred between 1992 and 2003, the 90-10 log wage gap would have swung by over 120 log points. Notably, firm entry and exit generally acted to increase earnings at the bottom end of the distribution more than at the top; in some cases, it worked to decrease earnings at the top. Ultimately, firm entry and exit resulted in a decline in the 90/10 ratio in each industry.

Finally, the effect of the sorting of workers and firms is apparent in a comparison of columns (4) and (5). Sorting of workers across different sets of firms generally worked to increase earnings inequality, depressing earnings at the lower end of each industry's distribution relative to those at the upper end. Indeed, sorting acted to increase 90th percentile earnings in three of the four industries.

Panel (b) of Table 3.7 reports the decompositions for the five industries in which overall earnings inequality increased. As was the case for the declining-inequality industries, worker churning had little effect on the earnings distribution in these sectors. Columns (2) and (3) in panel (b) show that increased experience lowered inequality by raising earnings more at the bottom than the top of the earnings distribution in each of the five industries. Interestingly, however, the impact of changing experience on earnings, while largely symmetric across the distribution within industries, was quite different across industries. For example, changes in experience boosted each earning percentile by nearly twice as much in log points in manufacturing than in services.

The effect of firm entry and exit was substantial in these five industries, and in general it led to a decrease in earnings inequality. Entry and exit of firms tended to raise earnings at the bottom more than at the top end of the distribution in each of the industries. In wholesale, the 90th percentile of earnings dropped considerably due to firm entry and exit. Finally, comparing columns (4) and (5) indicates that sorting of workers among firms generally led to an increase in inequality. Earnings at the bottom of the distribution were much lower due to sorting, which resulted in rises in the 90-10, 90-50, and 50-10 differences in all five industries. This effect was particularly large in manufacturing and services.

Overall, the decompositions in Table 3.7 show that, while trends in overall inequality diverged across industries, similar underlying factors were at work. Worker entry and exit had little effect on the wage inequality measures despite high levels of worker churning in the economy. Increased experience (as measured by the aging of workers) acted to increase earnings at all levels, but with a larger impact at the lower end of the distribution. Thus, increased experience tended to lessen wage inequality in all industries.

Firm entry and exit and sorting of workers were the biggest factors driving changes in earnings distributions, with the former acting to decrease inequality and the latter acting to increase it in most cases. That is, both in the aggregate as well as within most individual industries, the results lend support to a model of creative destruction that features ongoing assortative matching amid heavy firm entry and exit. That said, despite the similarities in the underlying factors driving changes in earnings distributions, the magnitudes of the effects differed considerably across industries.

The Kullback-Leibler measure of the divergence between probability distributions provides a useful aggregate summary statistic for comparing these trends and a means by which to substantiate our main results.[91] Table 3.8 presents the decomposition of the Kullback-Leibler measure between the 1992 and 2003 earnings distributions.

[91] The Kullback-Leibler measure for two density functions f_1 and f_2 is defined by $\int_0^\infty \left[f_1(w) - f_2(w) \right] \ln(f_1(w)/f_2(w)) dw$.

Table 3.8: Kullback-Leibler Distance Measure Decompositions by Sector 1992-2003

Sector	(1) Change from 1992 to 2003	(2) Worker Entry and Exit	(3) Change in Observable Worker Characteristics	(4) Firm Entry and Exit	(5) Sorting of Firms and Workers
Agriculture, Fishing, & Forestry	0.09	0.10	0.01	0.05	0.01
Mining	0.02	0.02	0.07	0.67	0.07
Construction	0.03	0.04	0.01	0.10	0.02
Manufacturing	0.04	0.04	0.07	0.32	0.06
Transportation & Communication	0.03	0.03	0.04	0.19	0.03
Wholesale	0.03	0.03	0.03	0.20	0.06
Retail	0.02	0.02	0.02	0.13	0.04
Finance, Insurance, & Real Estate	0.09	0.10	0.03	0.17	0.03
Services	0.02	0.03	0.01	0.19	0.06

Based on LEHD data for CA, IL, MD, and NC.

Consistent with our results, the Kullback-Leibler measures in Table 3.8 indicate that the largest shifts in earnings distributions between 1992 and 2003 occurred in agriculture, fishing, and forestry as well as in finance, insurance, and real estate. Further, the decomposition results in Table 3.8 suggest that worker entry and exit led to a modest increase in the distance between the 1992 and 2003 earnings distributions in mining, manufacturing, as well as transportation and communication, while leading to a slight decline or no change at all in the distance in each of the other industries. The effect of worker entry and exit appears to have been greatest in agriculture, fishing, and forestry; finance, insurance, and real estate; and services, where, as the results in Table 3.8 suggest, distances between earnings distributions would have been markedly larger had such entry and exit not occurred between 1992 and 2003. Notably, changes in the observable characteristics of workers tended to shrink the distance between the two distributions only for those three industries in which worker entry and exit tended to widen the distance.

As expected given the results using our decomposition methodology, firm entry and exit narrowed the distance between the 1992 and 2003 earnings distributions across all industries. That is, in all sectors of the economy, distances between earnings distributions would have been substantially larger had firm entry and exit not occurred between 1992 and 2003. In contrast, and once again consistent with earlier findings, assortative matching widened the distance across all industries; without the contribution of reallocation of workers across firms, earnings inequality within in each industry would have been considerably lower.

To summarize, earnings distributions changed differently across industries between 1992 and 2003. Worker entry and exit into an industry appeared to have little effect on the industry earnings distribution over the period, but firm entry and exit tended to compress within-industry earnings distributions. Meanwhile, sorting among firms and workers tended to result in greater dispersion in each industry's earnings distribution. Changes in the observable characteristics of workers, which in our data primarily reflect the aging of workers, led to increases in earnings across the distribution in all industries with mixed but generally muted effects on inequality.

Focusing in on the observed decrease in the 50-10 percentile difference, which occurred overall and across many industries, it appears as if at least a small portion of the decline was attributable to changes in observable characteristics. The remainder of the decrease occurred as the entry and exit of firms and changes in employee-employer matches had big but offsetting impacts; the negative impact of the firm turnover tended to dominate the positive impact of the change in employer-employee matches. The one factor that appears to have played a role in the increase in the 90-50 difference that we observed both overall and for many individual industries was sorting among workers and firms. Changes both in observable characteristics and in firm entry and exit tended to lower this difference.

3.7 Robustness

3.7.1 Workforce Characteristics and Mobility

Before concluding, it is important to note that the decomposition of changes in the earnings distribution, while accounting for worker entry and exit into an industry, do not account for the origins of workers who enter each industry and the destinations of those who exit. Workers can enter a particular industry either by leaving another industry or entering the sample over the period. Similarly, workers can exit an industry by moving to another industry or leaving the sample.[92] Those individuals who are new to the sample, those who exit the sample, those who switch industries, and those who remain in their industry over the 1992-2003 period may have systematically different characteristics, including both observable and unobservable characteristics, that could affect our interpretation of the decomposition results. Some data on the observed and unobserved measures of human capital for these industry entrants (leavers) as well as the pay policies of the firms they join (leave) appear in Table 3.9.

[92] Workers entering the sample can be new labor force entrants who resided in our group of states or migrants from other states. Workers leaving the sample can be workers leaving the labor force or workers moving to a state outside our group of states. Unfortunately, we cannot distinguish these different groups of sample entrants and leavers.

Table 3.9: Worker Sector and Sample Mobility
1992-2003

	Mobility Type	Number	Percent	Mean θ	Mean **xb** 1992	Mean **xb** 2003	Mean y 1992	Mean y 2003
Switchers	(switch sectors between 1992 & 2003)	2,523,443	9.6%	0.08	1.08	1.37	0.04	0.08
Entrants	(not in 1992 sample, in 2003 sample)	10,982,559	41.7%	-0.05		1.26		0.01
Exiters	(in 1992 sample, not in 2003 sample)	7,859,437	29.8%	0.02	1.15		0.04	
Stayers	(remain in sector between 1992 & 2003)	4,974,338	18.9%	0.24	1.16	1.38	0.09	0.09

Based on LEHD data for CA, IL, MD, and NC.

Among workers entering industries between 1992 and 2003, over 80% were individuals not in the sample in 1992. Relative to workers who remained in each sector between 1992 and 2003, industry entrants who were new entrants into the sample between 1992 and 2003 had both lower observed and unobserved skill levels, and furthermore tended to work at firms that paid less. While workers who switched industries between 1992 and 2003 also had lower unobserved skills and worked at firms that paid less than those who did not switch, the magnitude of the difference was considerably smaller than for those who were new entrants into the sample. Moreover, the observed skills of industry switchers were similar to non-switchers.

Among workers exiting industries between 1992 and 2003, over three-quarters left the sample. While sample leavers had lower unobserved skills than those who switched industries, their observed skill levels were slightly higher on average. Moreover, those that left the sample tended to leave firms that had pay policies similar to those from which industry switchers left.

3.7.2 Minimum Wage Effects

As previously mentioned, the large and offsetting effects of firm entry and exit and worker-firm sorting are most evident at the bottom end of the earnings distribution, which raises the possibility that the sorting adjustment is due to the substantial minimum wage hikes that took place exclusively in California during the sample period. While the federal minimum wage remained constant at $5.15 between 1997 and 2003, California increased its state minimum wage three times during the five-year span, the last time in January 2002 bringing it to $6.75. To check the robustness of the results given the possibility that California minimum wage legislation is behind the observed sorting adjustment, as well as to shed light on the potential influence of the change in minimum wage on industry earnings distributions themselves, we present results excluding California in Table 3.10.[93]

Consider first the services industry, which has a relatively large number of individuals working at or near minimum wage. If we include California, as in Table 3.7, the counterfactual that assumes there had been no entry and exit of firms implies that the log wage in services would change by 1.27 at the 10th percentile, where minimum wage legislation might be most likely to bind. Excluding California, as in Table 3.10, the same counterfactual suggests that the log wage would change by only 0.13. At the 50th percentile, meanwhile, the difference between the changes in log wages with California included (0.19) versus without California (0.01) is much smaller. Similarly, differences between the changes with or without California at the 90th percentile are negligible.

[93] For studies more closely examining the effects of changes in the real value of the minimum wage over time, see, for example, DiNardo et al. (1996) and Lee (1999).

Table 3.10: Decompositions of Changes in Earnings Distributions by Sector, Excluding California 1992-2003

Measure	(1) 2003	(2) + Worker Entry and Exit	(3) + Change in Observable Worker Characteristics	(4) + Firm Entry and Exit	(5) + Sorting of Firms and Workers	(6) 1992	(7) Change from 1992 to 2003
Agriculture, Fishing, & Forestry							
10th percentile	9.20	-0.02	0.17	0.26	-0.18	8.98	0.22
50th percentile	9.98	-0.02	0.14	0.06	-0.03	9.87	0.11
90th percentile	10.83	-0.05	0.09	-0.08	0.10	10.72	0.11
90-10 difference	1.63	-0.03	-0.09	-0.34	0.28	1.74	-0.11
90-50 difference	0.85	-0.03	-0.05	-0.14	0.14	0.85	0.00
50-10 difference	0.79	0.00	-0.03	-0.20	0.15	0.89	-0.11
Mining							
10th percentile	9.93	0.00	0.27	0.65	-0.47	9.91	0.02
50th percentile	10.65	0.00	0.19	0.16	-0.30	10.70	-0.05
90th percentile	11.14	0.00	0.14	0.00	-0.11	11.16	-0.02
90-10 difference	1.21	0.00	-0.13	-0.65	0.37	1.25	-0.04
90-50 difference	0.49	0.00	-0.05	-0.16	0.19	0.46	0.03
50-10 difference	0.72	0.00	-0.08	-0.49	0.18	0.80	-0.07

Table 3.10 (continued): Decompositions of Changes in Earnings Distributions by Sector, Excluding California 1992-2003

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Measure	2003	+ Worker Entry and Exit	+ Change in Observable Worker Characteristics	+ Firm Entry and Exit	+ Sorting of Firms and Workers	1992	Change from 1992 to 2003
Construction							
10th percentile	9.60	-0.01	0.17	0.55	-0.38	9.43	0.17
50th percentile	10.42	-0.02	0.16	0.14	-0.09	10.29	0.13
90th percentile	11.18	-0.02	0.09	0.01	0.02	11.04	0.14
90-10 difference	1.58	-0.01	-0.08	-0.55	0.40	1.61	-0.02
90-50 difference	0.76	0.00	-0.07	-0.13	0.11	0.75	0.01
50-10 difference	0.82	-0.01	-0.01	-0.41	0.29	0.86	-0.03
Manufacturing							
10th percentile	9.65	0.00	0.25	1.55	-1.55	9.54	0.11
50th percentile	10.38	0.00	0.24	0.10	-0.22	10.27	0.11
90th percentile	11.26	0.00	0.15	-0.25	0.08	11.08	0.18
90-10 difference	1.62	0.00	-0.10	-1.80	1.63	1.54	0.08
90-50 difference	0.88	0.00	-0.09	-0.34	0.30	0.81	0.07
50-10 difference	0.74	0.00	-0.01	-1.45	1.33	0.73	0.01

Table 3.10 (continued): Decompositions of Changes in Earnings Distributions by Sector, Excluding California 1992-2003

Measure	(1) 2003	(2) + Worker Entry and Exit	(3) + Change in Observable Worker Characteristics	(4) + Firm Entry and Exit	(5) + Sorting of Firms and Workers	(6) 1992	(7) Change from 1992 to 2003
Transportation & Communication							
10th percentile	9.69	0.00	0.20	0.27	-0.25	9.56	0.13
50th percentile	10.46	0.00	0.16	-0.09	-0.04	10.34	0.11
90th percentile	11.45	0.00	0.09	-1.04	0.86	11.25	0.20
90-10 difference	1.77	0.00	-0.11	-1.31	1.12	1.70	0.07
90-50 difference	1.00	0.00	-0.07	-0.95	0.91	0.91	0.09
50-10 difference	0.77	0.00	-0.04	-0.36	0.21	0.79	-0.02
Wholesale Trade							
10th percentile	8.96	-0.01	0.09	0.58	-0.50	8.87	0.09
50th percentile	9.86	-0.01	0.16	0.12	-0.09	9.77	0.09
90th percentile	10.83	-0.02	0.13	-0.14	0.12	10.74	0.09
90-10 difference	1.87	-0.01	0.03	-0.72	0.62	1.87	0.00
90-50 difference	0.97	-0.01	-0.03	-0.26	0.21	0.96	0.00
50-10 difference	0.90	0.00	0.06	-0.46	0.41	0.91	0.00

Table 3.10 (continued): Decompositions of Changes in Earnings Distributions by Sector, Excluding California 1992-2003

Measure	(1) 2003	(2) + Worker Entry and Exit	(3) + Change in Observable Worker Characteristics	(4) + Firm Entry and Exit	(5) + Sorting of Firms and Workers	(6) 1992	(7) Change from 1992 to 2003
Retail Trade							
10th percentile	9.72	-0.01	0.18	0.91	-0.78	9.54	0.18
50th percentile	10.50	-0.01	0.18	0.13	-0.10	10.27	0.23
90th percentile	11.62	-0.01	0.11	-0.17	0.23	11.26	0.36
90-10 difference	1.91	0.00	-0.08	-1.08	1.01	1.72	0.18
90-50 difference	1.12	0.00	-0.08	-0.30	0.33	0.99	0.14
50-10 difference	0.78	0.00	0.00	-0.78	0.68	0.73	0.05
Finance, Insurance, & Real Estate							
10th percentile	9.34	-0.03	0.14	0.25	-0.19	9.22	0.12
50th percentile	10.30	-0.03	0.13	0.06	-0.04	10.20	0.11
90th percentile	11.24	-0.02	0.06	-0.16	0.18	11.09	0.15
90-10 difference	1.90	0.00	-0.08	-0.42	0.38	1.87	0.04
90-50 difference	0.94	0.01	-0.07	-0.22	0.22	0.89	0.05
50-10 difference	0.96	0.00	-0.02	-0.19	0.16	0.98	-0.01

Table 3.10 (continued): Decompositions of Changes in Earnings Distributions by Sector, Excluding California 1992-2003

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Measure	2003	+ Worker Entry and Exit	+ Change in Observable Worker Characteristics	+ Firm Entry and Exit	+ Sorting of Firms and Workers	1992	Change from 1992 to 2003
Services							
10th percentile	9.83	-0.07	0.09	0.13	-0.18	9.82	0.02
50th percentile	10.46	-0.08	0.07	0.01	-0.06	10.45	0.01
90th percentile	11.07	-0.06	0.06	0.00	0.00	10.97	0.10
90-10 difference	1.23	0.01	-0.03	-0.13	0.18	1.15	0.08
90-50 difference	0.60	0.02	-0.01	-0.01	0.05	0.52	0.09
50-10 difference	0.63	-0.01	-0.03	-0.12	0.13	0.64	0.00

Entries in columns (2) - (5) report the change in the measure when the factor is either assumed not to have occurred (as with worker and firm entry and exit) or replaced by its 1992 value (as with observed worker characteristics and the conditional distribution of worker matches given a firm level of pay).
Based on LEHD data for CA, IL, MD, and NC.

On the other hand, while like the services industry, the retail trade industry has a large number of minimum wage workers, an examination of Table 3.10 reveals little evidence that similar patterns hold in each industry with respect to changes in the lower portion of the earnings distribution including and excluding data from California. However, an analysis of CPS data shows a substantial drop in the proportion of part-time workers in the retail industry, from 33% in 1992 to 22% in 2003. The observed differences in trends across industries might be due to a tendency among exiting retail firms to have hired a disproportionate number of part-time workers compared to entering firms. This explanation would focus more on hours than wages, and relies on the fact that part-time workers are more likely to be at the lower end of earnings distribution.

3.8 Conclusion

In this chapter, we use linked employer-employee data from the LEHD Program at the U.S. Census Bureau to explore changes in earnings distributions across sectors of the economy, paying particular attention to the way in which the reallocation of jobs and workers affect changes in earnings inequality. Our decompositions shed light on the extent to which changes in workforce composition, firm entry and exit, and job reallocation affect industry-specific earnings distributions. We also directly examine the degree to which changes in the matching of workers and firms affect earnings inequality.

While we document differences across industries in the magnitudes and directions of change in various aspects of the earnings distribution between 1992 and 2003, our earnings decompositions reveal that most factors had similar qualitative effects in each sector. In particular, even in industries in which there was very little change in the aggregate earnings distribution between 1992 and 2003, there were enormous, albeit offsetting, changes in the factors contributing to earnings change. The same factors that were at work in industries with declining earnings inequality tended to be at work in those with increasing inequality. The magnitudes of these effects, however, varied considerably across sectors.

More specifically, we find that worker entry and exit had very little impact on changes in the earnings distributions between 1992 and 2003 in each of the industries we examine. Despite the ample opportunities for firms to change their workforce compositions, industry workforces remained, by and large, very similar, and earnings gains due to experience tended to be higher at the lower end of the distribution. This does not lend credence to the notion that individual firms are changing their production technologies in a way that is biased towards skill.

Changes in observable characteristics, which mainly involved the aging of the workforce within each industry, tended to shift earnings distributions to the right. The effect of having an increasingly experienced workforce was to decrease earnings inequality in eight of the nine industries we consider, in each case primarily by increasing earnings at the bottom end of the earnings distribution.

On the other hand, the net impact of firm entry and exit was to reduce the dispersion of earnings for all industries. In nearly all industries, firm turnover acted to bolster earnings at the bottom end of the distribution relative to the top. To the extent that firm wage premia reflect rent sharing, unionization, and/or efficiency wage payments, it is difficult to reconcile the fact that firms pay these premia disproportionately to workers at the bottom end of the earnings distribution with a declining importance of wage setting institutions for low-wage workers. In addition, we do not find the changing sectoral earnings inequality in low-wage and highly unionized industries that would be consistent with hypotheses about the impact of changing unionization and real minimum wages.

Finally, sorting of workers based on the human capital measures over time tended to increase the dispersion of industry earnings distributions between 1992 and 2003. This is consistent with the idea that the driving force of economic change is the entry and exit of firms, and can be linked to the selection of new technologies, and the associated workforce, by new firms.

Our analysis, which uses new techniques to demonstrate the utility of employer-employee matched panel data in decomposing changes in earnings distributions over time, ultimately suggests that even when earnings distributions change little overall, the extensive amounts of worker and firm reallocation that have been documented in the literature do have large effects on different parts of the earnings distribution. In particular, the entry and exit of firms and sorting of workers and firms based on underlying worker skills are important determinants of changes in industry earnings distributions over time.

Appendix A

Model of Job Hopping, Earnings Dynamics, and Industrial Agglomeration

This appendix is devoted to developing the details of a model of industrial clustering that features a spatial dimension and industry-specific skills. The model, the basic setup and implications of which I present in Chapter 1 along with my empirical analysis, builds on models of on-the-job search pioneered by Burdett and Mortensen (1998) and extended by Postel-Vinay and Robin (2002a, 2002b).

A.1 Wage Outcomes Inside an Industry Cluster

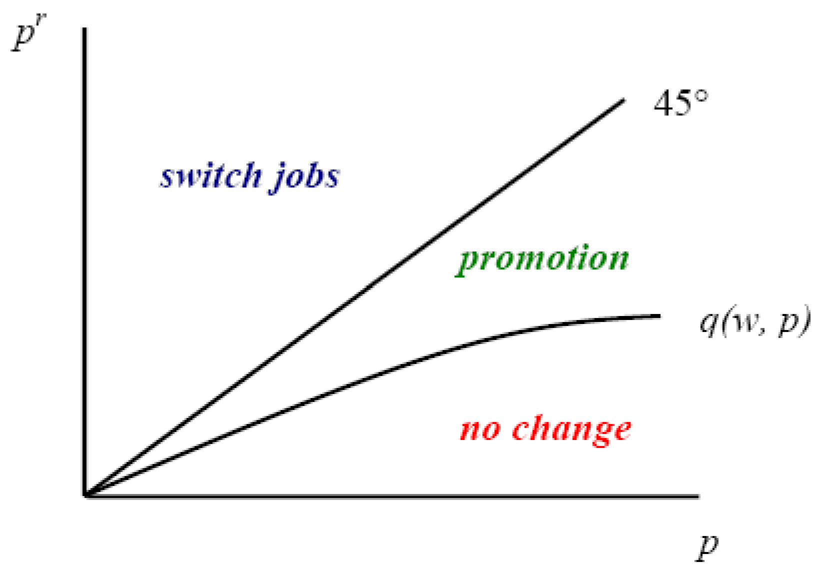
Let V_0 be the lifetime utility of a worker in industry L and let $V(w, p)$ be the utility of a worker when employed in industry H at a firm with productivity p at a wage w. Workers in the L industry receive wage offers from the sampling distribution $F(x)$ at a rate λ. Hence, with linear utility and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

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

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 $V(w'_0(x), x) = V_0$. Given this, the above expression collapses to $\rho V_0 = b$.

Workers in a cluster who are already employed in the H industry receive wage offers from the sampling distribution *F(x)* at a rate γ. Figure A.1 depicts the three different possible outcomes of Bertrand competition over a worker between two H-type firms in a cluster: a worker could switch jobs (when $p^r > p$), receive a wage increase at his or her current employer (when $q(w, p) < p^r \leq p$), or experience no change in his or her employment status or wage (when $p^r \leq q(w, p)$).[94]

Figure A.1: Possible Outcomes of Bertrand Competition



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 $V(p, p)$. Thus, a worker will move to a firm of type $p^r > p$ if the more productive firm offers at least the wage $w'(p, p^r)$ defined by

[94] For the figure, I assume for simplicity that F is uniform for the purposes of deriving $q(w, p)$. More generally, while $q(w, p)$ will always be increasing in p and will never cross the 45° line, it need not be concave.

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

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

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

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 her wage at the current firm; 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,

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

Integrating by parts yields

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

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,

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

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 $p^r > p$,

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

We can derive a similar equation for the offer made to a worker in the L industry who is earning b:

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

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

A.2 Wage Outcomes 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:

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

For all $x \in [p_{min}, p_{max}]$, we have that $V(w'_0(x), x) = V_0$. Substituting this into the above expression yields $\rho V_0 = b$. The lack of other H-type firms 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 Firm Employment[95]

We now turn to deriving steady state H-type firm employment 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 the employment rate in the L industry, denoted e, satisfies $e = \delta/(\delta + \lambda)$ since worker flows out of L, λe, must balance flows into L, $\delta(1-e)$.

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.[96]

In an unclustered region, an H-type firm employs labor such that $l^u(p\text{-}c|\, p) = l^u(b|\, p)$ for all $p \in [p_{min}, p_{mzx}]$. Hence, equating inflows and outflows of workers at the firm and recalling that there are M workers in each region, $\delta l^u(b|\, p) = \lambda eM$, which implies that in equilibrium, employment at an isolated H-type firm is a constant l^u.[97]

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

Let n denote the number of firms in a cluster. A worker that is employed at a clustered H-type firm with productivity p at a wage w could separate either for exogenous reasons (at a rate δ) or because that worker receives an offer from another H-type firm

[95] The model results from this point onward are very preliminary. Comments and suggestions are welcome.
[96] That is, $l^u(p) = \int_{w'_0(p)}^{p\text{-}c} dl^u(x|p)$ and $l^c(p) = \int_{w'_0(p)}^{p} dl^c(x|p)$.
[97] Of course, this expression for l^u is equivalent to $(1\text{-}e)M$.

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.

A.4 Firm Profits

Current operating profits in an isolated area, in which an H type firm must pay a recurring productivity cost per worker of c, sets wages equal to b, and employs l^u workers, are given by $\pi^u(p)$:

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

Clearly, operating profits are increasing linearly in p in an isolated region ($\partial\pi^u(p)/\partial p > 0$ and $\partial\pi^{u2}(p)/\partial p^2 = 0$).

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, canceling terms, and noting that $l^c(w| p) = l^c[q(w,p)|q(w,p)]$ since in equilibrium an H-type with productivity $q(w,p)$ has the same number of total employees that an H-type with productivity p has at a wage less than or equal to w, we arrive at the following expression for operating profits for an H-type firm in a cluster:[98]

$$\pi^c(p) = \{[(\delta+\gamma)\lambda\delta M]/[(\delta + \lambda)(\rho + \delta)n]\}$$

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

Applying Leibniz's rule and given that $\partial F(p)/\partial p > 0$, operating profits in a cluster are increasing at an increasing rate in p ($\partial\pi^c(p)/\partial p > 0$ and $\partial\pi^{c2}(p)/\partial p^2 > 0$). 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.

A.5 Endogenous Productivity

I endogenize productivity distributions in clustered and unclustered areas by permitting each firm to make investment choices that, in turn, feed into its individual productivity level.[99] I continue to take the fact that some firms are located in a cluster and

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

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

[99] This framework borrows from Postel-Vinay and Robin (2002b) and Acemoglu and Shimer (2000).

others outside a cluster as given, and show later that such a spatial distribution can arise in an equilibrium setting.

Suppose that firms are ex-ante identical, each possessing technology with constant returns to labor and decreasing returns to capital. In particular, suppose that output per capita for a firm with a capital stock of K is $p = f(K)$, where $\partial f(k)/\partial k > 0$ and $\partial f^2(k)/\partial k^2 < 0$. Further assume for the sake of simplicity that $f(K) = K^{\alpha}$, where $0 < \alpha < 1$. Then, taking the user cost of capital as an exogenous and constant rate r, total profits for an unclustered establishment with productivity p, $\Pi^u(p)$, can be written as

$$\Pi^u(p) = \pi^u(p) - rp^{1/\alpha}$$

Substituting for $\pi^u(p)$ and taking the derivative with respect to p, we arrive at the optimal investment choice outside a cluster:

$$\partial\Pi^u(p)/\partial p = (\lambda M)/[\delta + \lambda] - (r/\alpha)p^{1/\alpha - 1} = 0$$

Rearranging this expression yields p^u*,

$$p^u* = \{(\alpha\lambda M)/[r(\delta + \lambda)]\}^{\alpha/(1-\alpha)}$$

Together with equilibrium employment, optimal investment is constant for firms that disperse.

Profits for a clustered establishment with productivity p, $\Pi^c(p)$, can be expressed as

$$\Pi^c(p) = \pi^c(p) - rp^{1/\alpha}$$

or, substituting in for $\pi^c(p)$,

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

Inside a cluster, the optimal investment choice can once again be determined by the first order condition, which in this case is

$$\partial\Pi^c(p)/\partial p =$$
$$\{[(\delta+\gamma)\lambda\delta M]/[(\delta + \lambda)(\rho + \delta)n]\}\ [\{\rho + \delta + \gamma[1 - F(p)]\}/\{\delta + \gamma[1 - F(p)]\}^2]$$
$$- (r/\alpha)p^{(1-\alpha)/\alpha} = 0$$

With the lower bound of the distribution F being such that $1 - F(p_{min}) = 1$, the first-order condition at p_{min} becomes

(1) $$\{(\lambda\delta M)/[(\delta + \lambda)(\rho + \delta)n]\}\ [(\rho + \delta + \gamma)/(\delta + \gamma)] = (r/\alpha)p_{min}^{\ (1-\alpha)/\alpha}$$

which solves as

$$(2) \qquad p_{min}^{c*} = \{[\alpha(\rho + \delta + \gamma)\lambda\delta M]/[r(\delta + \lambda)(\rho + \delta)(\delta + \gamma)n]\}^{\alpha/(1-\alpha)}$$

The distribution of productivities arising from the first order condition (1) and such that the minimal productivity in the cluster satisfies (2) represents an equilibrium solution.[100] No firms have an incentive to deviate by choosing an investment level that yields productivity lower than p_{min}^{c*} nor one that yields productivity greater than p_{max}^{c*}, as $p < p_{min}^{c*}$ results in an inability to attract sufficient workers to offset investment costs and $p > p_{max}^{c*}$ results in sufficiently high investment costs to overwhelm any gains in terms of attracting a greater number of workers (given the convexity of $p^{1/\alpha}$).[101]

Hence, inside the cluster, firms' dispersed investment choices give rise to productivity dispersion in equilibrium, while outside the cluster investment choices are identical and productivity dispersion is not present.

A.6 The Spatial Distribution of Firms

To derive the distribution of firms across locations, I impose the condition that profits inside the cluster must equal profits outside the cluster and must be driven to zero.

---

[100] See Postel-Vinay and Robin (2002b) for a formal proposition of this equilibrium solution.
[101] At the upper bound, $1 - F(p_{max}) = 0$, yielding the following:

$$\{[(\delta+\gamma)\lambda M]/[\delta(\delta + \lambda)n]\} = (r/\alpha)p_{max}^{(1-\alpha)/\alpha}$$

which solves as

$$p_{max}^{c*} = \{(\alpha\lambda(\delta + \gamma)M)/[r\delta(\delta + \lambda)n]\}^{\alpha/(1-\alpha)}$$

Note that

$$p_{max}^{c*}/p_{min}^{c*} = \{[(\rho + \delta)(\delta + \gamma)^2]/[\delta^2(\rho + \delta + \gamma)]\}^{(1-\alpha)/\alpha}$$

which implies $p_{max} = p_{min}$ if $\gamma = 0$.

This results because of free entry and exit and the freedom of firms to choose their locations.

Equilibrium profits for firms outside the cluster are

$$\Pi^u* = [(p^u* - c - b)\lambda M]/(\delta + \lambda)] - r(p^u*)^{1/\alpha}$$

or, substituting in for p^u*,

$$\Pi^u* = (1 - \alpha)(\alpha/r)^{\alpha/(1-\alpha)}[\lambda M/(\delta + \lambda)]^{1/(1-\alpha)} - (c + b)[\lambda M/(\delta + \lambda)]$$

Using $p_{min}{}^c*$, optimal profits inside the cluster are

$$\Pi^c* = \{[(p_{min}{}^c* - b)(\rho + \delta + \gamma)\lambda\delta M]/[(\delta + \lambda)(\rho + \delta)(\delta + \gamma)n]\} - r(p_{min}{}^c*)^{1/\alpha}$$

or, substituting in for $p_{min}{}^c*$,

$$\Pi^c* = \{[(\{[\alpha\lambda\delta(\rho + \delta + \gamma)M]/[r(\rho + \delta)n]\}^{\alpha/(1-\alpha)} - b)(\rho + \delta + \gamma)\lambda\delta M]/$$
$$[(\delta + \lambda)(\rho + \delta)(\delta + \gamma)n]\} - r(\{[\alpha\lambda\delta(\rho + \delta + \gamma)M]/[r(\rho + \delta)n]\}^{\alpha/(1-\alpha)})^{1/\alpha}$$

and rearranging,

$$\Pi^c* = (1 - \alpha)(\alpha/r)^{\alpha/(1-\alpha)}\{[(\rho + \delta + \gamma)\lambda\delta M]/[(\delta + \lambda)(\rho + \delta)(\delta + \gamma)n]\}^{1/(1-\alpha)}$$
$$- b\{[(\rho + \delta + \gamma)\lambda\delta M]/[(\delta + \lambda)(\rho + \delta)(\delta + \gamma)n]\}$$

In the long run, free entry and exit drive profits across locations to zero. Setting $\Pi^c* = 0$ yields $n*$ as a function of the parameters of the model:

$$n* = [(1 - \alpha)/b]^{(1-\alpha)/\alpha}\{[\alpha(\rho + \delta + \gamma)\lambda\delta M]/[r(\delta + \lambda)(\rho + \delta)(\delta + \gamma)]\}$$

Given that there is some range of values such that $n* > 1$, there exists an uneven geographic distribution of firms in which some cluster and some disperse. Further, from the condition $\Pi^u* = 0$, we have $c*$, the differential that must exist to sustain such a distribution:

$$c* = (1 - \alpha)\{\alpha\lambda M/[r(\delta + \lambda)]\}^{\alpha/(1-\alpha)} - b$$

This productivity differential in favor of labor in clustered firms could stem from local workers' increased exposure to the industry, social networking, or any other form of endowment or spillover that might give rise to geographic variation in industry workforce quality.

Appendix B

Data Details and Sample Descriptive Statistics for Job Hopping, Earnings Dynamics, and Industrial Agglomeration

B.1 Data Details

In Chapter 1, I use 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. Ideally, my sample would cover as many states as possible. Although I have corroborated my results with data for four additional states, the computational burden of pooling individual and establishment-level panel data across multiple states are considerable. Still, I hope to expand the sample geographically in future work.

Geographic coding in my sample state, while better than in many other states, is not perfect. Roughly 88% 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 at the county level.

Throughout the analysis, I use the sample of establishments for which we have accurate rooftop address information. I experimented with more inclusive samples of establishments, in which I assigned the latitude and longitude of the centroid of the lowest level of geography possible to those businesses without rooftop coordinates. Overall, this changed the results little, though there was evidence that "heaping" of establishments in geographic centroids sometimes biased clustering statistics upward and resulted in spurious patterns of agglomeration. While using a more restricted sample eliminates this problem, it is worth noting that the sample of rooftop-confident establishments is not a random sample of units. In general, geographic information tends to be worse for establishments in rural regions, establishments in slower-growing areas, and establishments that are part of larger multi-unit firms. See Freedman et al. (2006) for further details.

B.2 Sample Descriptive Statistics

Table B.1 presents statistics on sample establishments and job spells. 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 males in establishment workforces inched slightly higher during the decade, while the average fraction of whites edged lower. The average of mean within-establishment educational attainment levels, though high compared to many other sectors, declined over the sample period. Consistent with the statistics aggregated to the establishment level, the descriptive statistics for job spells 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 and dispersion in earnings, however, rose markedly between the early 1990s and the early 2000s.

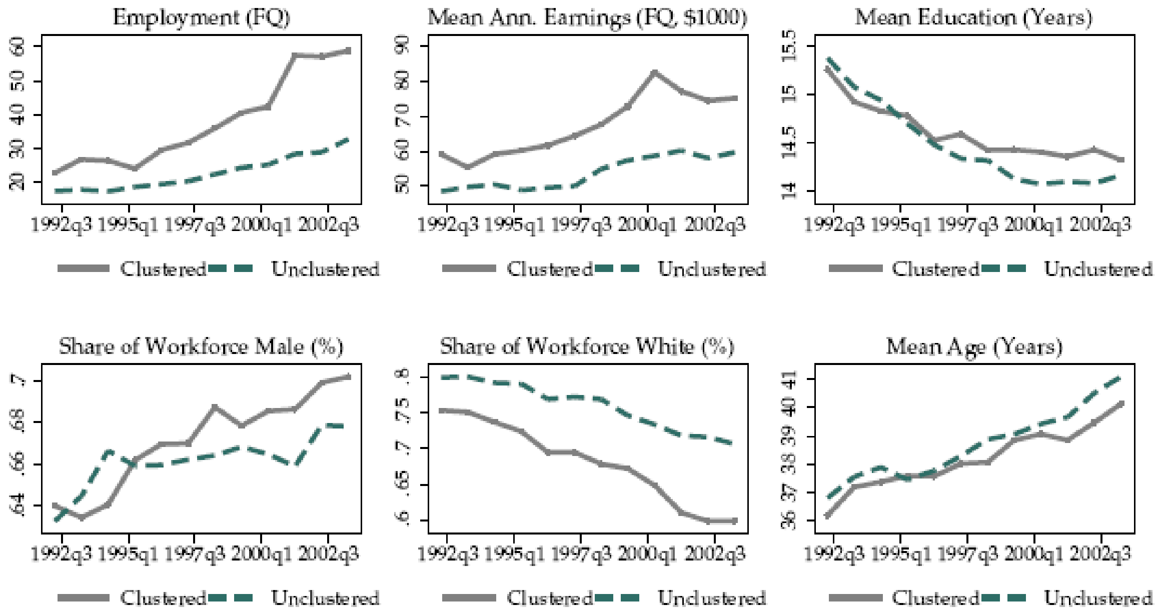
Table B.1: Software Industry Sample Descriptive Statistics
NAICS 5112

	1992Q2	2003Q2
Software Establishments	822	882
Mean Employment	20	46
Share with 1-4 Employees	0.48	0.55
Share with 5-19 Employees	0.32	0.24
Share with 20-49 Employees	0.12	0.1
Share with 50+ Employees	0.08	0.11
Share in Metropolitan Area	0.84	0.87
Software Workers	19,234	40,364
Share Male	0.61	0.65
Share White	0.75	0.58
Mean Age	35	38
Mean Annualized Earnings ($1997)	61,392	97,302

Based on LEHD data.

Workers and firms in clusters differ from those outside clusters along several observable dimensions. As shown in Figure B.1, 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. Hence, central to the empirical analysis is controlling for worker and firm heterogeneity across locations in an effort to isolate the effects of clustering on labor market dynamics.

Figure B.1: Workforce Characteristics of Clustered and Unclustered Software Establishments
NAICS 5112, 1991-2003



Clustering defined with employment-based LQs using a 25-mile radius.
Based on LEHD data.

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