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

Fredrik Andersson, Cornell University,
Matthew Freedman, University of Maryland,
John Haltiwanger, University of Maryland and NBER,
Julia Lane, National Science Foundation,
Kathryn Shaw, Stanford University and NBER

November 28, 2005

Thanks to Tim Bresnahan, Ben Campbell, Phil Hardiman, Edward Lazear, Paul Oyer and seminar participants at Stanford University, Washington State University, UC Santa Barbara, the Society of Labor Economics meetings, for their helpful comments. 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 document is released to inform interested parties of ongoing research and to encourage discussion of work in progress. This research is a part of the U.S. Census Bureau's Longitudinal Employer-Household Dynamics Program (LEHD), which is partially supported by the National Science Foundation Grant SES-9978093 to Cornell University (Cornell Institute for Social and Economic Research), the National Institute on Aging Grant 5 R01 AG018854-02, and the Alfred P. Sloan Foundation. The views expressed herein are attributable only to the author(s) and do not represent the views of the U.S. Census Bureau, its program sponsors or data providers. Some or all of the data used in this paper are confidential data from the LEHD Program. The U.S. Census Bureau is preparing to support external researchers' use of these data; please contact U.S. Census Bureau, LEHD Program, Demographic Surveys Division, FOB 3, Room 2138, 4700 Silver Hill Rd., Suitland, MD 20233, USA.

1. Introduction

In the new economy, information products and services are inherently a risky business. Developing the latest new information product that is widely adopted has enormous payoffs – at the same time developing a new product that languishes with little use is very costly given the time and high skilled workers required to develop new products. Software products are the poster child for this phenomenon in the new economy with video games at or near the top of the list for such high stakes product development. For example, the latest release of Grand Theft Auto (Vice City) has had more than $200 million in revenues but most games earn much less. Not all software products can ever be high winners however. Business applications software (e.g., database software) is still a risky business but much less risky than video games. Getting a foothold in this product niche is critical but once applications have been adopted, software producers have an installed base that provides a degree of stability for the future of their product development.

Developing these products that might win big is like to require the most talented software developers. Using a rich new longitudinal matched employer-employee data source that permits tracking of outcomes for both firms and workers in the software industry, we investigate the connection between the payoff distribution of the products and the earnings of the software workers. We measure the earnings and employment outcomes for workers over time so we can measure the earnings growth due to within firm pay increases and job hopping between firms. Our measures of earnings include the contribution of exercised stock options and bonuses, which are important components of compensation in this industry. We have rich and detailed information about the product mix of each of the firms and revenue outcomes for each of the firms so that we can measure the potential payoff distribution and the actual payoffs for each firm based upon its product mix. We use this rich data source to investigate the connection between high stakes products and the stars in the software industry.

The theoretical motivation for the empirical analysis begins with the assumption that all innovative firms want workers who are good at designing or picking new projects. The key insight of the model is that some firms value this talent much more than other firms do (Lazear 2005). If the firm is operating in a product market in which innovation is rarely rewarded – or in which even a great project has little return – then the payoff distribution is low variance and the value of talent is low. On the other hand, if the firm is operating in a product market in which the payoff distribution has a high variance – as it does in the video game example above – then the firm values talent highly because talented workers who pick projects well can win the most in markets where there are huge potential payoffs. The prediction is that those firms operating in high variance payoff markets will hire more talent, and thus will pay higher wages.

Our unique microeconomic data enables us to look inside firms and see what the innovative high potential payoff firms are doing to attract and reward star talent. First, we show that the high potential payoff firms are paying more in starting salaries than other firms. These firms are selecting "star" software workers who themselves have a history of prior success (i.e. selecting workers who have a personal history of high wage levels and high wage growth rates). Second, we show that high potential payoff firms are rewarding workers for loyalty – they are rewarding workers for staying with the firm. Our findings show that "star" software workers, who achieve the highest pay levels, do so through loyalty – these workers stay with their firm and receive higher levels of performance pay. There is also an institutional side that produces this loyalty – firms in the software industry tie workers with deferred pay in the form of stock options that vest after four years.

It has been rare for researchers to have data that links the product market strategy of the firm to the compensation or human resource management practices of the firm. This has been done largely in the literature on CEO pay, where data is available, and the literature documents CEO pay-for-performance as a function of firm size or underlying strategies. There have been isolated instances in which researchers have done 'insider' studies in some firms in which they have documented a link between strategy and performance (Hubbard and Baker (2003), Stern (2003), Wulf (2002, 2005), Garicano and Hubbard (2005), etc.), or have used survey data to do so (MacLeod and Parent (1999)). There is also an increasing focus on knowledge workers, as they become an increasingly dominate part of the U.S. economy (Chevalier and Ellison (1999), Garicano and Hubbard (2005), Fallick, Fleischman, and Rebitzer (2005), Lerner and Wulf (2005)) But typically there has been a major gap between the theoretical models and the empirical models of incentive contracts and sorting. That is, each theoretical model of some form of incentive pay states the assumptions under which that form of pay is optimally adopted, but empirical researchers may, at best, show that some firms succeed with incentive pay, but do not empirically model its adoption. We show that incentive pay plans and sorting aimed at high talent are optimal when the firm's strategy is to operate in high potential payoff product markets.

In short, we show that firms that operate in innovative high payoff product markets will select star workers and will pay stars both higher starting salaries and higher performance pay. These innovating firms put a lot of money up front in the form of salaries for talent because they are betting on a high stakes game of producing the winning high-payoff products. Of course, these high-stakes firms control the probabilistic outcomes: they pay for performance by sorting workers, or by paying high wages to attract the best talent so the probability of winning is higher for them. They also pay for stars with performance pay with experience and with requirements of loyalty, which increases the probability that they will win the game. As a result, these firms playing in the high-stakes market for innovations cause income inequality to rise. When one of their projects hits it big, customers around the world buy that project and it is hugely profitable. That makes the talent at innovative firms hugely valuable, and thus increases the variance of pay dramatically for starting salaries and increases experienced pay *ex post* for winning the innovation competition. The highest skilled stars are much more highly valued and paid than those who are slightly less skilled.

The paper proceeds as follows. In the next section, we provide some background basic facts about the software industry that help motivate our approach and analysis. Our application of the Lazear (2005) model is sketched in Section 3. A detailed description of the data is provided in section 4. The empirical specifications we explore and the results from these specifications are presented in Sections 4 and 5. Concluding remarks are provided in section 6.

2. Background Facts

We present some basic facts in this section that help motivate the approach and analysis that follows. These facts are aimed at describing the revenue payoff distribution for firms and the wage distribution for workers in the software industry.

First, firms pay a lot for star software workers. That is, software firms pay very high wages to a subset of workers. The top half of Table 1 provides summary statistics about the distribution of income from the 2000 Decennial Census Public-Use Microdata Sample (PUMS) for workers in all industries and in the software industry.[1] Workers in the software industry as a whole earn more than twice what workers in all other industries earn (looking at either the mean or median). However, these Census data do not measure earnings that are important in software – performance bonuses and stock options. Thus, in the bottom half of Table 1, we use data for workers in the software industry from employer-filed Unemployment Insurance (UI) records, which contain data on all earnings including bonuses and stock options.[2] Because these UI data do not contain hours of work or occupation information, we limit our sample to workers earning at least $50,000 in the software industry.[3] While no longer comparable workers, the addition of bonuses and options raises median earnings to over $95,000 for software workers. But most important, it raises mean earnings for experienced workers to $344,268. Thus, the top of the pay scale is very high – firms pay a lot for star software workers.

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[1] We focus on full-time workers between 21 and 44 years of age.

[2] These data are from the Longitudinal Employer-Household Dynamics (LEHD) Program and are described in detail in our data section below.

[3] The $50,000 cutoff is discussed in more detail below, but note that based on Decennial Census PUMS data, two-thirds of all software workers and four-fifths of software engineers (Census occupation code 102) have total earnings of at least $50,000. When we replicate the mean of total earnings in Table 1 using only those software engineers, it is little changed, rising from $90,668 in the table to $103,881. Note finally that the $50,000 is the worker's earnings when we last observed him or her in the data – 36 percent of those earning $50,000 or more when we last observe them have starting salaries less than $50,000. Fortunately, Table 1 (as well our robustness analysis discussed in more detail below) shows 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.

Table 1

	Mean	Median	90th	SD
2000 Decennial Census - Workers 21-44, 35+ Hours/Week & 35+ Weeks/Year(in 2001 dollars)				
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 Publishing Industry (NAICS 5112)				
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 (102) in the Software Publishing Industry (NAICS 5112)				
Total Earnings	90,668	70,691	138,193	369,374
Wage and Salary Income	90,496	70,160	138,193	369,777

	Mean	Median*	90th*	SD
Unemployment Insurance (UI) Data - Workers 21-44, Earning $50,000+ Annualized (in 2001 dollars)				
Software Publishing Industry (NAICS 5112)				
Starting Annualized Earnings (Excludes Left-Censored)**	69,353	59,665	108,692	82,432
Experienced Annualized Earnings (Censored and Uncensored)***	344,268	95,508	310,644	2,051,985
One-Year Prior Annualized Earnings (Censored and Uncensored)****	199,172	86,796	220,760	1,101,658
Top Decile of Workers (by Last Observed Earnings) in Software Publishing Industry (NAICS 5112)				
Starting Annualized Earnings (Excludes Left-Censored)**	107,660	80,899	184,951	142,526
Experienced Annualized Earnings (Censored and Uncensored)***	2,532,500	670,993	6,688,470	6,064,204
One-Year Prior Annualized Earnings (Censored and Uncensored)****	750,551	171,642	1,338,380	2,862,843

* Average within a 10% band around the true percentile

** Starting Earnings with a new employer, quarterly data converted to annual.

*** Earnings for Experienced Employee with an average of five years of tenure, last quarter of employment, quarterly data converted to annual.

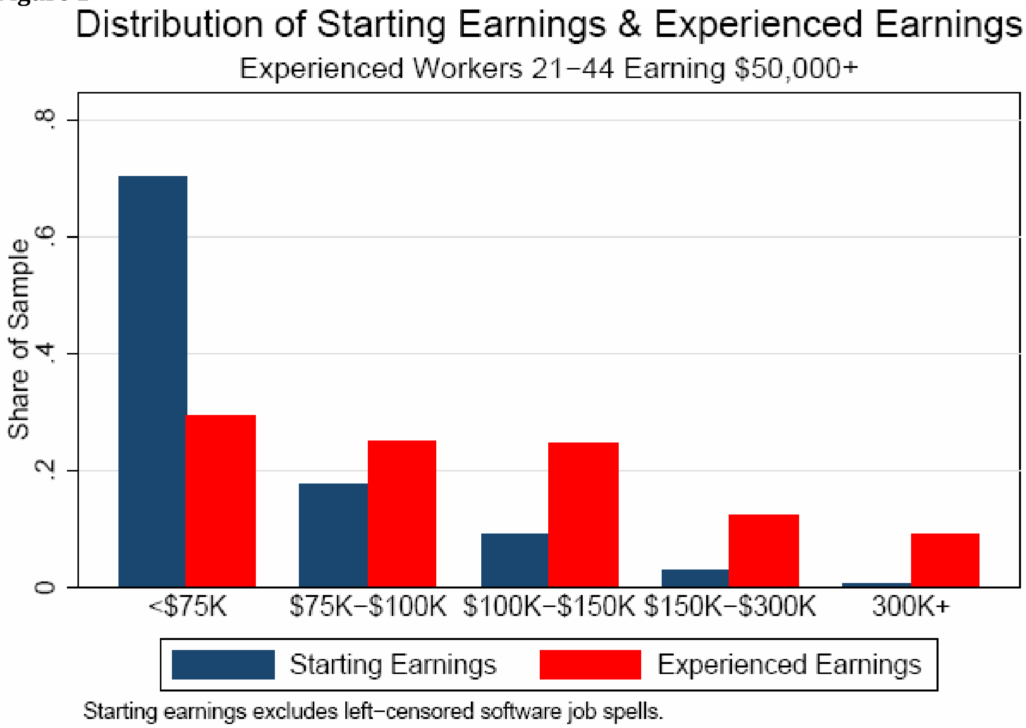
**** Annualized earnings three quarters prior to last observed full quarter.

Total Number of Software Spells in UI Data	51,859
Number of Spells Not Left Censored	43,620

Second, the pay of software workers rises markedly with tenure. Figure 1 compares the earnings distribution for starting salaries to the distribution for experienced-workers earnings (based on the UI data containing options, and exact values are given in the bottom half of Table 1). While 70% of starting earnings are below $75,000, only 29% of experienced workers earn below $75,000, where 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. Since starting salaries include the salaries paid to new but experienced workers, earnings rise markedly with tenure.[4]

[4] For now, we include both censored and uncensored spells for experienced earnings but exclude left-censored spells for starting earnings. In subsequent sections, we control for censoring in all of the empirical specifications relating earnings outcomes.

Figure 1



Third, there appears to be a high variance to the gains to innovation in the software industry. The distribution of revenues for the top ten video games are shown in Table 2. The distribution is highly skewed –even restricting attention to the top ten games of 2002, the top game earned nearly five times as much as the bottom. We have selected video games as an illustrative example; not all software firms should have such a skewed payoff distribution for their products. For example, firms that produce enterprise resource software for large mainframe computers would have a lower variance payoff. Consider the SAS Institute, producing statistical software for the businesses. They sell their software through licenses to firms, and that they had about a 97% renewal rate (Stanford GSB case, 1997). In mainframe enterprise software, large firms have locked into a software provider and purchase it year after year – so the provider is profitable, but software product innovations do not have huge upside potential gains. In contrast, in the consumer video game market, the costs of consumers switching to a new 'hot' game is minimal – firms in this market have huge upside potential if the product does 'hit' in the market. In our data below, we will measure differences in the skewness of potential payoffs for different software product lines, but to motivate our theory below, we use video games to illustrate some prima facie evidence that they may be significant.

Table 2: Top Video Games, Ranked by 2002 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 Hawks	Activision	$46

In what follows, we provide a model that links these facts—that links the skewness and high pay of software workers to the skewness of firm's payoff distributions. Our model posits that firms in markets like video games should hire 'stars,' because a star is one who can create and select innovative products, and the gaming industry has the upside sales potential that they will earn the most from great new innovations.

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 uncertainty—not knowing whether an innovative product will pay off. In software innovation, two groups of employees must select projects: software developers begin working on a new software project not knowing whether they will develop a great product; and software managers allocate funds to research projects not knowing whether the product will succeed in the market. Thus, a model of project selection pertains to the work of managers and software programmers (or developers).

Given uncertainty about whether projects will be successful, the key role of an employee seeking to make innovations is to create or pick the best projects. The model by Lazear (2005) demonstrates how employees who are the best at creating or picking projects should be sorted among firms operating in high variance payoff markets.[5] Assume that projects can have two outcomes, a good outcome with probability P, and a bad outcome with probability (1-P). A product portfolio produces a distribution of revenue shown in Figure 2: a portfolio with a lot of bad projects produces low revenue to the left and a lot of good projects produces high revenue. The uncertainty derives from the fact that software engineers and managers do not know which are the good projects and which are the bad projects. As a result, they can make two types of error: "false positive errors" in accepting projects that they believe are good, H', but that later turn out to be bad; and "false negative errors", 1-H, in which they can reject a project that would have turned out to be a good project.

More specifically:

[5] Similar ideas have been raised before, notably by Prendergast (2000, 2002)

1-H ≡ 1-Probability (accepting a project | project it is actually good) ≡ false negative

H' ≡ Probability (accepting a project | project it is actually bad) ≡ false positive

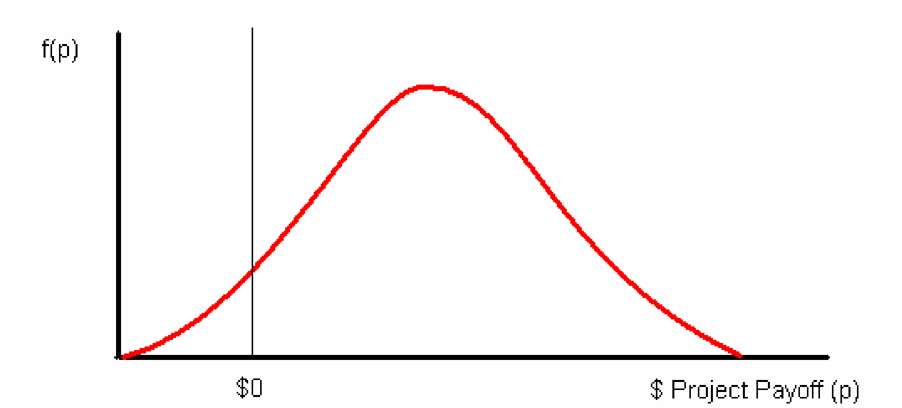
If the firm chooses to undertake a good project and it pays off, the firm earns \$X. If the firm chooses to undertake a project that turns out to be a bad one, it costs the firm -\$Y. The firm has zero costs and zero revenue if rejects projects early. Given these probabilities and net revenues, the expected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

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

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

This payoff structure is defined in Figure 2: firms that achieve a high payoff are located in the upper tail of the Payoff distribution there are the firms that have a high value of PHX. Firms that fail are those that have a high value of the losses (1-P)H'Y.

Figure 2: Project Payoff Distribution



So what is the value of talent or skills in these firms? Lazear (2005) defines a star as one who has a higher probability of accepting good projects when they really are good, and a lower probability of accepting bad projects. Thus, a

(H + ε) ≡ Star worker's Probability (accepting a project | project it is actually good)

(H' - ε) ≡ Star worker's Probability (accepting a project | project it is actually bad)

Where high ε is the measure of the quality of the star – the talent that person has in picking projects relative to non-stars.

Therefore, the value of selecting a star employee relative to a non-star employee is the incremental expected payoff, Δ:

$\Delta \equiv$ value of selecting a star

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

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

Thus, 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 from having stars with extra talent ε. This conclusion is displayed in Figure 3. The bold line in the Figure 3A shows a high variance payoff distribution and the bold line in Figure 3B shows a low-variance payoff distribution. The dotted (or blue) line is the change in the distribution from star talent. The left tail shifts right due to stars because there are reductions in false positives – or the star reduces by ε the probability H' of losing (1-P)Y (so the star does not approve or produce projects that later fail because they were "truly" not good projects). The right tail shifts right because the star reduces the number of false negatives: the 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 PA1 to PA2 in the payoff distribution of Figure 3A. This is the gain to paying for or hiring stars—and that gain must exceed the cost of the star employee. Figure 3B depicts a narrower underlying project payoff distribution, which would arise when projects are less risky and thus losses and gains are smaller. When a star shifts this low-risk payoff distribution due to their talent or project assessment, the mean gains are smaller; in that case, the gains are PB2-PB1. As is evident in the figures, the gains to stars are smaller in low-risk product markets than in high risk: (PB2-PB1) < (PA2-PA1). In sum, stars are more valuable in high-risk product markets of Figure 3A than in low-risk product markets of Figure 3B, because there are bigger gains (or lower losses) to the assessment or discovery of great projects in high-risk markets.

Figure 3: Shifts in the Payoff Distribution Due to Reductions in False Positive or False Negative Errors

Figure 3A: More Risky Payoff Distribution

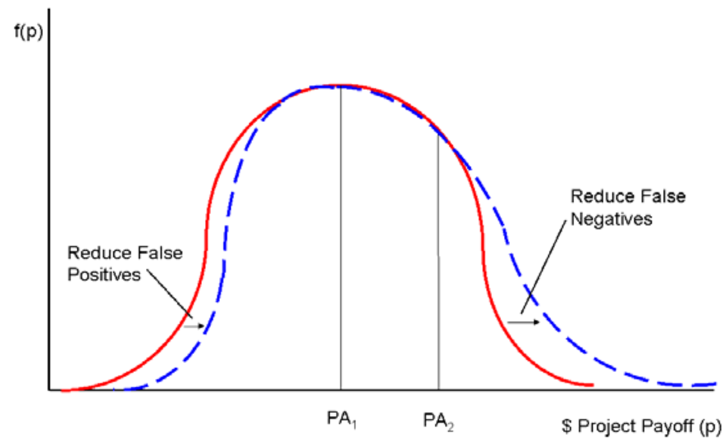
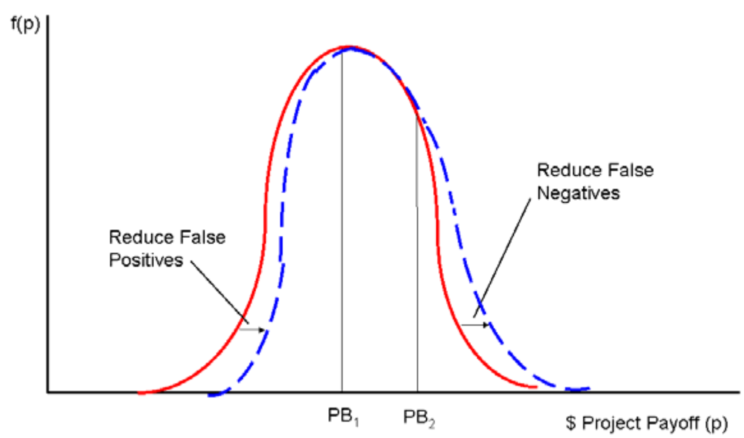


Figure 3B: Less Risky Payoff Distribution



In making the link from star talent to product market outcomes in this model, we have defined as someone with the skills to pick great projects, but where do these skills come from? The ability to pick projects could come from innate talent, or it could be developed as human capital on the job through learning, or it could arise from higher effort in response to incentives. In all these cases, higher talent should be rewarded with higher wages.

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.

Thus, underlying this hypothesis is the point that firms in high variance product markets have human resource practices that select, develop, and reward highly skilled software workers. We do not observe firms' human resource practices, but we do observe in our data all the wages within each software firm that reflect these practices.

4. Data

To study the connection between the structure of firm's product strategies and skill demand, we build a data set with detailed information on the earnings and employment histories of workers as well as on product market characteristics for the firms at which these workers are employed. We take advantage of a unique employer-employee matched data set constructed and maintained by the U.S. Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) Program, and augment it with highly detailed firm characteristics from the Economic Census and worker characteristics from the 2000 Decennial Census. Appendix 1 provides further details on each of these data sets as well as on our approach to integrating the data.

The Prepackaged Software Industry

We test the hypotheses of our model by focusing on the prepackaged software industry, which corresponds to the four-digit SIC 7372 (NAICS 5112). This narrow focus has a number of key advantages. First, the software industry as a whole has a high variance payoff structure, which is illustrated by the video game products in Table 2. As we show below in our results, there are substantial rewards to producing the new hot product. Many traditional industries, such as automobile manufacturing, have segments that are R&D intensive, but in software we can examine the entire firm as one R&D intensive unit that has a potentially high variance payoff to innovation. A second and related advantage of studying software is that we can directly trace the performance of the primary employees, including software developers and managers, to the payoff structure of the firm. In other industries, the "knowledge" workers are a smaller component of employment and have a less direct impact on the output of their firms.

A third advantage of studying software is that in the Economic Census surveys it conducts every five years, the Census Bureau collects a broad array of information on firms that produce software. . Thus, for the software industry, there is detailed product-line information (described below) that we use to construct a measure capturing the variation in the payoff structure by product. These data also provide measures of the size and age of software firms.[6] These are likely to be important controls that are correlated with product market strategies.

[6] We thank Ron Jarmin for kindly sharing information on firm and establishment ages with the LEHD Program for this project.

The Software Dataset on Workers and Establishments

The data on software workers is derived from the larger data base of individual records within firms created by the LEHD project housed at the Census Department. The LEHD's longitudinal wage data base is derived from the quarterly records of the employment and earnings of individuals from the unemployment insurance (UI) systems data, matched to internal administrative records containing information on workers' date of birth, race, and sex.

These data have several advantages. First, since the scope of the LEHD data is virtually the full universe of employers and workers, the movements of workers through the earnings distributions within firms as well as across firms can be tracked accurately. Second, the earnings data represent the earnings the worker is actually paid, not his memory of his earnings.

A third key advantage of these administrative data is that the earnings measures are quarterly and include bonuses and exercised stock options. Previous studies have never before included stock options data for a wide range of workers across firms. And although the earnings information does not include fringe benefits, all bonuses are included. Our compensation data include the value of all options when they are exercised, or when the employee cashes in the options and receives the value. We do not have data on when options are granted to employees. We would argue that in some sense, exercised options are the preferred measure of pay for our analysis, not options granted to employees since, as Oyer and Schaefer (2005) point out, it takes four years for stock options to be fully vested. In a typical example for a software company, the options are worth nothing for the employee's first two years, and then are vested at a rate of 2 percent a month for the remaining three years (Russell 2005).[7] Thus, the value of options granted depend on two uncertain outcomes – on whether the employee stays with the firm until the options are vested, and on the growth of the stock price of the company. No comprehensive data set (for non-executives) contains data on options granted, and ours is the first paper to use data that contain information on options exercised. In most employment contracts, employees must exercise all options within 90 days of leaving their firm; our data follows employees for those 90 days and thus contains the data for all exercised options [recall that "experienced" earnings represent earnings from the last FQ of a worker's spell, so if those options are exercised in the very last weeks of employment or after an employee actually departs the firm, then we will not see them].

It is important to emphasize that the LEHD data capture the full universe of employers and workers; they are not merely a sample of software workers or firms. That is, by law the UI data on workers contain all employed workers for the states in our study. However, when we look at certain specific features of workers or of firms in the software industry, our data set becomes a smaller sample of the population of workers and firms.

Our basic universe of data on workers follows software workers through 83,497 spells of employment for ten states in the U.S. from approximately 1992 to 2001 (where the exact starting years vary by state). The ten states were selected as states having large numbers of software

[7] For very detailed analysis of options granted and other forms of pay within a large software company, see Russell (2005). She shows, for example, that people who have large option grants are also likely to have exercised options (because they are older).

workers and a sufficiently large number of years that we can construct worker earnings histories from which to make meaningful inferences. Our primary results are based on two smaller datasets of 51,589 workers and of 26,276 workers. 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 workers in the prime of their careers with similar educational vintages. This reduces the sample from 83,497 to 67,452 workers. Second, we limit we limit our data to those workers making more than $50,000 at the end of their 1997 spell. The UI data does 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 the more skilled occupations, we choose those making more than $50,000. Appendix 1 contains an extensive discussion supporting our decision to limit the sample in this way. Together, the age and earnings limitations reduce the sample to 51,589 workers. Finally, while most businesses in our sample of workers could be successfully matched to the Economic Census, a smaller subset had complete information on the establishment, including size, age, sales, and detailed product line information. There are 26,276 workers for which we have complete information regarding worker characteristics as well as firm characteristics. All told, 688 software firms are represented in this sample.[8]

Lastly, we also construct a subset of data of employees in software occupations based on the occupational information in the 2000 Decennial Census. For this sample, we limit or data to those individuals in the software industry who are software engineers, developers, or managers (irrespective of earnings)**,** dropping those who are in other occupations within the software industry. Because the Decennial Census is a 1 in 6 sample of the population in 2000, our sample falls to 2,638 workers in software occupations. This smaller dataset is used to check our results using the larger data set discussed above, and thus the results using these data are referred to in footnotes below.

Measuring Earnings Levels and Earnings Growth

A major advantage of the administrative 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 periods of time. These unique data permit us to capture multiple facets of worker earnings profiles. In modeling the link between product markets and compensation, we use information on workers' earnings trajectories within firms, earnings growth associated with transitions between firms, and earnings levels for new and old workers in the firm.

We use five measures of earnings 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

[8] Throughout this paper, 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.

employment with each employer (with the dollar values at annualized 2001 dollars).[9] Another earnings measure is end-of-spell earnings,[10] which is aimed at measuring the earnings of experienced workers. Because end-of-spell earnings potentially contain exercised stock options, as workers must exercise their options within 90 days of quitting, an alternative measure is earnings one year prior to the end of the spell. This measure is intended to capture earnings of experienced workers before options are exercised. Earnings growth within the firm, or within-job earnings growth, is the difference between end-of-spell and beginning-of-spell earnings.[11] Finally, we measure between-job earnings growth as 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.[12]

Table 3 provides a summary of the basic statistics of these earnings level and earnings growth measures. As in Table 1, the skewness in the distribution is quite marked. Unlike Table 1, this table contains left-censored spells.

Table 3: Earnings Levels and Growth Among Software Industry Workers

Number of Observations	*Summary Statistic*	*First Observed Annualized Earnings*	*Last Observed Annualized Earnings*	*One-Year Prior Annualized Earnings***	*WJWG in Software Spell*	*BJWG into Software Spell*
51,859	Mean	$69,750	$344,268	$199,172	0.14	0.23
	Median*	$58,414	$95,508	$86,796	0.10	0.16
	90th Percentile*	$108,172	$310,644	$220,760	0.33	0.76
	St. Dev.	$89,887	$2,051,985	$1,101,658	0.18	0.55

* Average within a 10% band around the true percentile.

** Annualized earnings three quarters prior to last observed full quarter.

Measuring the Product Market Payoff Dispersion for Firms

The other important component of the hypothesis requires estimates of the variance of the expected payoff for the product market 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. Establishments in the Census are asked to provide data on its revenue for each of the thirty product lines, and we exploit this revenue information to construct a measure that reflects the variance of payoffs in each product category.

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[9] Beginning-of-spell earnings capture new workers to the firm and censored data of new workers in our data. 16 percent of the beginning-of-spell earnings are censored.

[10] We measure this as a worker's last full quarter of annualized earnings in a given spell. End-of-spell earnings captures workers leaving the firm and censored data when our observations end: 40 percent of the end-of-spell earnings are censored.

[11] 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.

[12] 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).

Each firm's *Product Payoff Dispersion* is created in two steps. First, for each of the thirty product classes, we calculate the 90/50 ratio of the log of revenue per worker. Because firms have multiple products, we treat each product within each firm as though it were a separate product revenue stream, and calculate the 90/50 ratio for the thirty product markets. Second, for each firm, we calculate its payoff dispersion in the product markets in which it is operating by weighting the product-specific 90/50 ratios for the thirty products by the percent of revenue that the establishment has in each product class. More specifically,

$$\textit{Product Payoff Dispersion}_i = \sum_{j=1} [\%\text{Revenue}_{ij}](\text{Product Revenue Dispersion}_j)$$

where $\%\text{Revenue}_{ij}$ is the percent of firm i's revenue coming from product class j, for product classes j = 1,..30, and where the product-specific variance is

$$\text{Product Revenue Dispersion}_j = \ln(\text{revenue}_{j,\,90}/\text{worker}_{j,\,90}) - \ln(\text{revenue}_{j,50}/\text{worker}_{i,\,50})$$

where Product Revenue Dispersion for product j is calculated across all firms producing in product class j, where each product line within each firm is treated as if it is its own independent firm. See Appendix 1 for details.

There are a few key features of the firm-specific *Product Payoff Dispersion* measure. First, this measure reflects each firm's actual product mix, but not its actual revenue. The payoff measure reflects the skewness of revenue per worker in the product classes in which the firm operates. A firm with a high *Product Payoff Dispersion* measure is not necessarily a high or low performing firm, but rather has a product mix with a right skewed distribution of payoffs. Also notably, the measure of revenue dispersion in a given product line is the 90-50 ratio, because the 90-50 ratio is a simple way of capturing the skewness of the upper tail of the revenue distribution. While our model in Section 3 refers to the variance of the entire distribution (thus the lower tail as well), we focus on the upper tail because we do not observe firm's losses – revenues are truncated at zero.

Table 4: Differences in Payoff Distributions By Product Line*

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

*Based on the national sample of firms.

The means of the *Product Payoff Dispersion* are reported in Table 4 for the highest risk and the lowest risk product lines. The means in Table 4 suggest that one element of our model is borne out: there is variation in the skewness of revenues across product classes.

5. Empirical Model

The model in Section 3 implies that firms operating in product markets with highly dispersed payoffs will hire more highly talented (star) workers. This model generates several testable hypotheses for the empirical analysis.

Product-Specific Payoffs

First, we should observe that 'star' talent is sorted into firms with a high payoff dispersion because these firms value the star skills the most. That is, the probability of hiring star workers will be:

(1) $P(S_i)_{jt}=\beta_0 + \beta_1\sigma^p{}_j + e_{ijt}$

where $P(S_i)_{jt}$ is the probability by firm j of hiring a star worker i that has a skill level of S_i at time t, and $\sigma^p{}_j$ is the payoff dispersion or variance that firm faces in its product market(s). It is important to remember that the payoff dispersion measure captures the variance of payoffs *in the firm's product class(es)*, and does not merely represent the firm's actual historical variance of success. When we turn to the data, $\sigma^p{}_j$ will not vary over time: it will be observed in one year and represent a firm-specific fixed effect identifying the product class or classes of the firm.

Second, individuals' wages should be higher in firms with higher observed payoff dispersion. A standard human capital wage equation is the following

(2) $\ln(W)_{ijt}= a_0 + a_1S_{ijt} + u_{ijt}$

where wages are a function of skills, but skills are unobserved to the econometrician. Because highly skilled workers will sort to the high payoff firms that value skills the most, payoff dispersion will serve as a measure of unobserved skills in the wage regression:

(3) $\ln(W)_{ijt}= \alpha_0 + \alpha_1(\sigma^p{}_j) + \varepsilon_{ijt}$

where $\sigma^p{}_{jt}$ is the product payoff dispersion. Thus, high payoff firms pay higher wages because they are selecting highly skilled workers

Third, wages should be more sensitive to the firm's payoff dispersion for more highly skilled workers. In software companies, it is the top talent (or the brilliant programmers) who should be paid the most for their skills in the firms operating in product markets with high payoff dispersion. This suggests a quantile regression: among low-wage workers, pay should not be a function of the firm's payoff dispersion (because worker sorting is irrelevant), but among high-wage workers it should:

(3') $\ln(W)_{ijt} = \alpha_0 + \alpha_1^{skill}(\sigma^p_j) + \varepsilon_{ijt}$

where α_1^{skill} permits the estimation of the rising sensitivity to payoff potential with skill at each point in the wage distribution.[13]

Fourth, earnings growth should rise with the firm's payoff dispersion. Though we do not have models of human capital investment or the use of incentive contracts that together determine pay, our model provides some possible predictions as to why software firms in high variance product markets might have high base pay that rises sharply with tenure. First, these firms should offer higher base pay because they value skills or talent more than do other firms, so they are selecting more highly talented people. Second, pay might rise markedly with tenure for these high variance firms for several reasons. The variance of pay should rise with tenure due to sorting. As in all matching models, the return to tenure is high because the stars are paid more over time and the losers are fired. Wages should furthermore grow as a function of greater human capital investment. Since people may be working in teams in which their skills are likely to be complementary with the other team members, and given that it takes time to identify star talent in the firm, firms will reward heavily for tenure. Finally, firms in these high variance product markets may also pay more for effort; that is, firms may have steep incentive pay contracts. In fact, case study evidence suggests that they do – a larger percent of a workers' pay is performance based as the skill level rises (Russell 2005). Lastly, literature on the software industry suggests that firms in the sector want teams to stay together for the product cycle, that they do not want to lose star talent, and that they want to provide incentives for effort.[14] Software firms therefore intentionally tie employees to the firm by granting stock options that vest slowly (typically over four years; this further steepens the wage-tenure profile for workers. In sum, it is possible that firms operating high variance product markets should pay more for loyalty: they should compensate their employees for staying with the firm more so than do firms in low-variance product markets. Thus, we also estimate

(4) $\Delta\ln(W)_{ijt} = \delta_0 + \delta_1^{skill}(\sigma^p_j) + \eta_{ijt}$

where $\Delta\ln(W)_{ijt}$ is wage growth within the firm with tenure.

Note finally that a positive coefficient, α_1 on σ^p_j, in (3) could reflect a compensating differential for risk, though there are numerous reasons why it would represent a return to skills as opposed to a return to risk taking (where risk is variance in income). We must think carefully about how much the variance of returns in the product market translates into pay variation for software workers. Typically, workers in software are rewarded for upside gains, but they are not penalized for losses – base pay typically does not fall when the firm loses money. Therefore, software workers are usually choosing between two alternative pay packages in job offers: a) low base pay, but high performance-based pay; b) high base pay, but no possibility of rewards if the worker or company do well. Thus, if firms operating in high variance product markets want to

[13] This point is also made in Buchinsky's (1994) model of wages in which he shows that the returns to education are higher at high wage quantiles, though the returns to experience are lower at high wage quantiles. Hallock, Madalozzo, and Reck (2004) show that among CEOs, the sensitivity of wages to firm performance rises as one moves up the earnings distribution.

[14] Russell (2005) and Cusumano and Selby (1995), Hoch, et al (2000), Stross (1997).

Deleted: Microsoft books.

induce high performance by offering incentive contracts, then contract (a) will be offered, implying high variance firms will have *lower* starting salaries (which are base pay) than firms in low-variance product markets. On the other hand, our model states that firms operating in high variance product markets will want to select the highest quality workers, and quality is unobserved to the econometrician, so these firms will have *higher* starting salaries (which are base pay) than firms in low-variance product markets. In sum, if the coefficient α_1 is positive for starting salaries, it is likely to reflect a return to skills in those product classes, not a return to risk taking.[15] For experienced workers, high pay could reflect a return to risk taking – if these workers took lower starting salaries with the hope of future uncertain gains.[16] Moreover, we have one further test as to whether firms are paying for talent versus risk-taking: if firms operating in high variance product markets hire more stars as hypothesized in equation (1), where 'star' talent is based on past jobs not current income at risk, then hiring reflects a return to skills or talent, not risk-taking. We return to this point when we estimate the probability of hiring stars by firms.

Firm-Specific Payoffs

The model implies that innovating firms pay higher wages *ex ante* (prior to success) when these firms operate in product markets that are high variance. However, often there is also an implicit

[15] There is one way in which a firm's losses will translate into lower pay for the worker – the worker will get fired and lose their returns to firm-specific human capital if the firm fails. But this too should produce a compensating wage-risk differential for experienced workers, not for young workers who have yet to invest in firm-specific skills. The lore in this industry is that there are workers who are risk-takers – who seek firms who might produce big hits as in our model – and that these risk-takers accept jobs that offer lower starting salaries for their skills, but that might produce big income gains. Using extensive data for one large software company, Russell (2005) shows 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 the less skilled.

[16] Note also that in jobs with a higher variance of returns for firms, some models would produce the conclusion that there should be less incentive pay in these high variance markets, or less pay at risk. Aggarwal and Samwick (1999) show that when the variance of stock market returns rises for a company, the percent of pay at risk (or performance pay) falls for top executives—there is a negative relationship between riskiness and pay. But they have a different kind of risk in mind, and their data measure a different kind of risk—their riskiness is the variance in stock returns due to noise or uncontrollable outcomes. It is true that 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, the variance of payoff outcomes could arise in part from an idiosyncratic shock representing noise or luck, but most importantly arises because some firms hire smarter 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 (not luck), so the coefficient α_1 on $\sigma^p{}_j$, should be positive, not negative. Prendergast (2000, 2002) also makes the point that higher risk environments may have more performance based pay, not less, because in those environments, the cost of determining what inputs to monitor is greater than the cost of utilizing output performance based pay. Since the source of the variance in payoffs cannot be identified (and we do not have time-series data product-specific variances or firm-specific variances), we turn to the data to determine the sign. For related empirical models of the risk-pay incentive relationships, for executives see Baker and Hall (2004), Core, Guay, and Ittner, Lamber and Larcker (2003), Murphy (1986), Schaefer (1998), and Wulf (2005), and for reviews see Hallock and Murphy (1999) and Murphy (1999).

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or explicit contract (through options) with employees that they will be rewarded for the firm's *actual ex post* success.[17]

A firm is successful *ex post* when it actually achieves high revenue – when its revenue per employee is high. Thus, we add to our model the firm's actual success affecting the level and growth of wages:

(4) $\ln(W)_{ijt}= \alpha_0 + \alpha_1^{skill}(\sigma^p_j) + \alpha_2^{skill}R_j + \varepsilon_{ijt}$

where R_j it the firm's actual revenue per employee. Note that endogeniety issues cloud the interpretation of this revenue per employee variable – high-wage workers with more talent are more likely to produce high revenues per employee R_j. As such, we primarily consider the addition of this variable as a control – that is, we are interested in exploring whether the impact of the payoff potential measure is robust to controls for the *ex post* revenue, R_j, of the firm. Because we do not have time series data on the firm's revenue (only one cross-section in 1997), we cannot test models that introduce variation in wages as a function of variation in the firm's revenue. Thus, we interpret R_j as a firm-specific control. However, previous data in manufacturing shows that there is far more cross-sectional variance than time series variance in productivity for firms (Foster et al. 2001).

5. Empirical Results

The primary hypotheses of the model are borne out by our empirical analysis using longitudinal data on software workers and the firms at which they are employed. We begin with wage results, then worker sorting, and conclude with additional evidence on the variance of wages within firms.

The Earnings Levels of Software Workers

The wage regression results in Table 5 show that earnings levels and within-job earnings growth rates rise with the firm's product payoff dispersion. Recall from the data description above that the firm's product payoff dispersion is the revenue-weighted 90-50 percentile ratio of revenue per person across the product markets in which the firm operates. All wage regressions control for the person's tenure, censoring of observed tenure, and age, and regressions in every second column also control for firm age, firm size, indicators of the density, education and industrial diversification of the county and in the worker outcome regressions dummies for quarters of accessions and separations to abstract from any macro effects, and the churning rate of jobs in the firm.[18]

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[17]In fact, many software firms are quite clear about this – if your project fails, you may still get promoted if you are talented and exerted effort. For case study evidence, see Microsoft (Stanford case), and for a theoretical model, see Gustavo (2005).

[18] The dependent variable in these regressions is the earnings residual for each spell in the sample, where the residual is from a regression of log earnings on quadratics of tenure at job, tenure in industry, and age, fully interacted with each other and with appropriate left and right censoring dummies. See the wage regression results in Appendix 2. Using the residual is equivalent to introducing these controls in the wage regression, but the residual is more intuitively appealing than raw earnings because it reflects only that component of earnings that cannot be accounted for by basic observable worker characteristics. We also appeal to the residual in the star probability

Looking at the regressions for *experienced workers earnings* (columns 1 and 2) and *starting salaries* (columns 3 and 4), we see that the *product payoff dispersion* variable has a very significant positive effect on each measure of earnings. Thus, even among new hires, firms with high payoff dispersion are paying higher wages, suggesting that they are selecting more skilled workers. There is extensive industry testimony to the software industry's very careful and deliberate hiring practices aimed at identifying the right talent, and it is also likely that careful selection reflects the high-commitment work environment of the industry (Day, Mang, Richter, and Roberts, 2004). In addition, the strong coefficient on dispersion for starting salaries suggests that firms operating in high payoff product markets are selecting more talented workers, not that they are paying compensating wage differentials for risk taking; if they were paying for risk-taking, the coefficient on the product payoff dispersion measure should be negative because risk-takers are taking lower starting salaries in exchange for the possibility of higher future options values (see Section 5 above).

Comparing the wage results for *experienced workers earnings* (columns 1 and 2) and *starting salaries* (columns 3 and 4), we reach the conclusion that earnings are much more sensitive to the product payoff dispersion for experienced workers than for new hires. The earnings for experienced workers can be very large by the end of their spell with the firm: 10 percent of software workers earn more than $310,000 at the end of their spells (Table 3). The very large wage payoffs for experienced workers could reflect a number of factors: higher marginal products (as in our model) a tournaments reward structure, participating in a high performance team, or improved selection of talented workers over time in the firm. We cannot identify the differences, but Russell (2005) provides very detailed evidence for one software company that all of these factors enter the earnings of software workers.[19] The point is that in each case, the person who can create or pick the best projects will have more skills and more incentive pay in firms with high product payoff dispersion.

regressions used below. When the churning rate is added, it is defined as the accession rate plus the separation rate less the absolute value of the net growth rate of employment at the firm. This churning or excess worker turnover rate is included as a control, since churning may be part of the interaction of product mix and internal labor market strategies that in turn impact the structure of wages. For example, high-risk product strategies may be associated with a high worker turnover. By including this control, we mitigate concerns that the payoff potential variable is capturing a compensating differential for high turnover.

[19] 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 is 33 and tenure ranges from 2.7 to 3.1 over 1996 to 1999, and about 65 percent were in research and development and 30 percent in management or administration. Though no previous studies are available describing in detail the forms of incentive pay for software workers, Russell (2005), provides evidence form a case study of one large software firm. She shows that pay is a function three things – base pay and the merit increases in base, bonuses, and stock options. In this firm, individual pay levels and individual deferred pay is very highly positively correlated within the firm (Russell, 2005, Figure 23). This example suggests that software companies use a combination of promotion-based pay, as in a tournaments model, of individual-level incentive pay, and of group-based incentive pay. Since these forms of performance pay rise with the grade level and rise the pay level in the firm, they suggest that performance bonuses are higher for star employees, both in their allocation (as in options granted) and in the realization (as in the value of bonuses and exercisable options). As a result, in our wage regressions, the wage growth or levels should contain a portion of wage gains that are attributable to performance-based pay (as will be described in more detail below).

The regression results for experienced workers may be heavily influenced by the inclusion of exercised stock options in the earnings measure. To test the sensitivity of our results to the inclusion of options, we run an additional regression in which experienced earnings are redefined as those for people one year before they quit their job or prior to dropping out of our sample due to censoring (since options are most likely to be exercised when departing a firm. The magnitudes of the coefficients in the experienced-earnings regressions decline somewhat, but the basic results remain.

Table 5a: Quantile Regressions for Earnings Level Residuals for Software Spells

	End of Spell Earnings "Experienced Earnings"		*Beginning of Spell Earnings "Starting Salaries"*		*One-Year Prior Earnings "Lagged Earnings"*	
	(1)	(2)	(3)	(4)	(5)	(6)
	All Firms	All Firms	All Firms	All Firms	All Firms	All Firms
Tenth Percentile						
Product Payoff Dispersion +	0.3226	0.3068	-0.1693	-0.0678	0.1070	0.0456
	(0.0481)**	(0.0460)**	(0.0434)**	(0.0570)	(0.0453)*	(0.0494)
Log Revenue per Worker	0.0622	0.0288	0.0386	0.0385	0.0485	0.0290
	(0.0045)**	(0.0104)**	(0.0045)**	(0.0066)**	(0.0043)**	(0.0079)**
Firm Average Worker Churn	1.1692	1.4403	0.9172	0.4170	0.5065	0.8833
	(0.1354)**	(0.1534)**	(0.1651)**	(0.1691)*	(0.1293)**	(0.1441)**
Fiftieth Percentile						
Product Payoff Dispersion +	0.3750	0.3715	0.1469	0.1631	0.2701	0.2581
	(0.0450)**	(0.0480)**	(0.0372)**	(0.0346)**	(0.0513)**	(0.0515)**
Log Revenue per Worker	0.1477	0.0874	0.0332	0.0457	0.0883	0.0634
	(0.0043)**	(0.0079)**	(0.0026)**	(0.0057)**	(0.0037)**	(0.0076)**
Firm Average Worker Churn	2.7335	3.3058	0.8869	0.7091	2.6445	2.8104
	(0.1423)**	(0.1555)**	(0.0894)**	(0.1016)**	(0.1490)**	(0.1326)**
Ninetieth Percentile						
Product Payoff Dispersion +	0.7420	0.7218	0.2083	0.2841	0.6391	0.5398
	(0.0962)**	(0.1180)**	(0.0457)**	(0.0563)**	(0.0930)**	(0.1002)**
Log Revenue per Worker	0.6406	0.1469	0.0820	0.0626	0.2847	0.1372
	(0.0171)**	(0.0168)**	(0.0041)**	(0.0078)**	(0.0116)**	(0.0128)**
Firm Average Worker Churn	1.3797	3.9577	0.8751	1.7865	1.5848	3.1629
	(0.2876)**	(0.2621)**	(0.1460)**	(0.1492)**	(0.2843)**	(0.2583)**
Ninety-Fifth Percentile						
Product Payoff Dispersion +	1.0363	0.6729	0.2803	0.2902	0.6727	0.6290
	(0.2365)**	(0.1689)**	(0.0677)**	(0.0727)**	(0.1260)**	(0.1425)**
Log Revenue per Worker	0.8205	0.1378	0.1107	0.0748	0.4431	0.1137
	(0.0166)**	(0.0322)**	(0.0073)**	(0.0153)**	(0.0159)**	(0.0229)**
Firm Average Worker Churn	0.9527	4.2284	0.6759	2.0844	1.3174	3.4670
	(0.3737)*	(0.4450)**	(0.2310)**	(0.2331)**	(0.3657)**	(0.3663)**
Controls++	No	Yes	No	Yes	No	Yes
Observations	26276	26276	26276	26276	26276	26276

All dependent variables are wage residuals from regression controlling for age and tenure (see Appendix 2).
Standard errors in parentheses. * significant at 5%; ** significant at 1%. Marginal Effects are reported.
+ Weighted 90/50 Ratio of Log Revenue per Worker in Firm's Product Lines
++ Controls include (log) firm employment; (log) firm employment squared;
Dummies for firm age (<6 years old, 6-10 years old, 11+ years old, with <6 omitted);
firm employment growth rate; a dummy for whether the firm is in a high density, high education,
and industrially diversified county; and year and quarter job separation dummies.

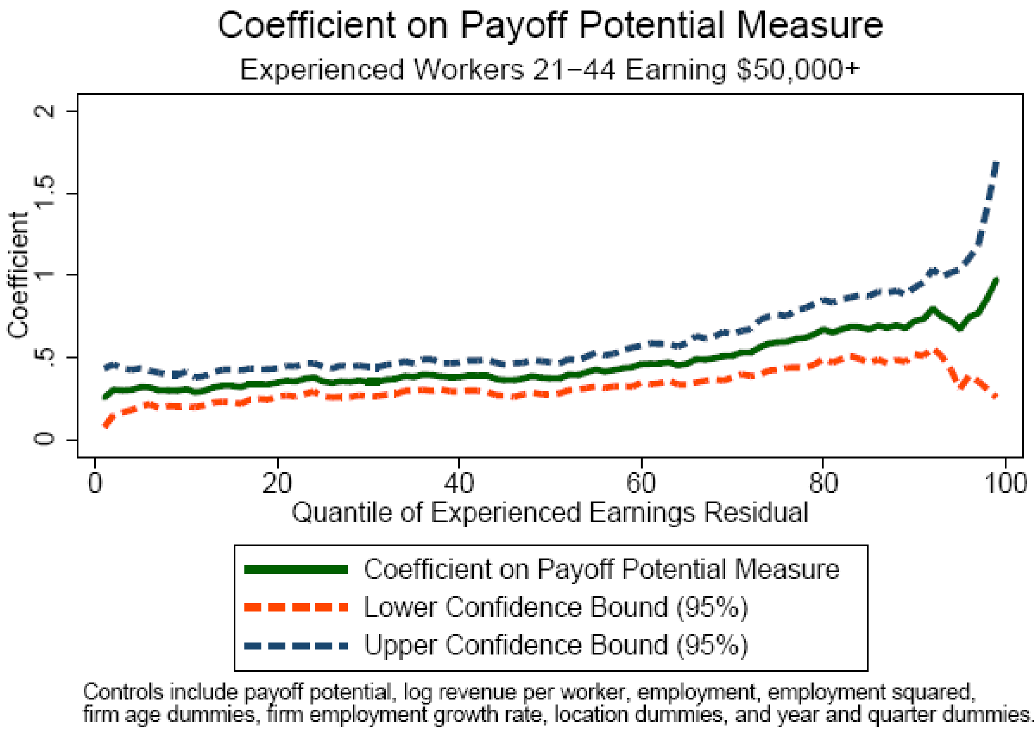
Table 5b: Quantile Regressions for Growth Rate Residuals for Software Spells

	Within Job Earnings Growth		*Between Job Earnings Growth*	
	(7)	(8)	(9)	(10)

	All Firms	All Firms	All Firms	All Firms
	Tenth Percentile			
Product Payoff Dispersion +	-0.0055	-0.0063	-0.2828	-0.1768
	(0.0068)	(0.0083)	(0.0676)**	(0.0567)**
Log Revenue per Worker	0.0034	-0.0040	-0.0216	0.0232
	(0.0008)**	(0.0016)*	(0.0080)**	(0.0124)
Firm Average Worker Churn	0.0271	0.1419	0.1269	-0.0886
	(0.0207)	(0.0272)**	(0.2350)	(0.2488)
	Fiftieth Percentile			
Product Payoff Dispersion +	0.0882	0.0716	-0.2070	-0.1636
	(0.0077)**	(0.0078)**	(0.0291)**	(0.0356)**
Log Revenue per Worker	0.0162	0.0015	0.0054	0.0254
	(0.0008)**	(0.0009)	(0.0032)	(0.0059)**
Firm Average Worker Churn	0.2539	0.3678	0.2765	0.1494
	(0.0257)**	(0.0166)**	(0.1031)**	(0.1167)
	Ninetieth Percentile			
Product Payoff Dispersion +	0.2543	0.2949	-0.2194	-0.1650
	(0.0264)**	(0.0346)**	(0.0939)*	(0.0873)
Log Revenue per Worker	0.0887	0.0245	0.0057	-0.0042
	(0.0027)**	(0.0047)**	(0.0097)	(0.0174)
Firm Average Worker Churn	0.6998	1.1196	0.5118	0.6335
	(0.0762)**	(0.1063)**	(0.3064)	(0.3640)
	Ninety-Fifth Percentile			
Product Payoff Dispersion +	0.2251	0.3123	-0.1651	-0.2133
	(0.0435)**	(0.0519)**	(0.2776)	(0.2728)
Log Revenue per Worker	0.1125	0.0369	0.0232	0.0228
	(0.0040)**	(0.0091)**	(0.0269)	(0.0473)
Firm Average Worker Churn	0.7821	1.4663	0.8609	1.1838
	(0.1194)**	(0.1655)**	(0.6226)	(0.6138)
Controls++	No	Yes	No	Yes
Observations	26276	26276	10803	10803

All dependent variables are wage residuals from regression controlling for age and tenure (see Appendix 2).
Standard errors in parentheses. * significant at 5%; ** significant at 1%.
+ Weighted 90/50 Ratio of Log Revenue per Worker in Firm's Product Lines
++ Controls include (log) firm employment; (log) firm employment squared;
Dummies for firm age (<6 years old, 6-10 years old, 11+ years old, with <6 omitted);
firm employment growth rate; a dummy for whether the firm is in a high density, high education,
and industrially diversified county; and year and quarter job separation dummies.

Figure 4:



The impact of the payoff potential rises with skill level – software workers at the upper reaches of the earnings distribution gain the most from working in high variance payoff firms, though workers at the median gain as well.[20] The sharply increasing impact of the payoff potential is illustrated in Figure 4 for experienced earnings; the coefficient at the 90th percentile is more than twice as large as the coefficient at the 10th percentile.

We turn next to the effect of the firm's actual revenues on wages. The wage regression results show that workers are paid more when the firm does succeed; indeed, pay rises very significantly as a function of the firm's actual log revenue per employee, *Log Revenue per Worker*.[21] The quantile analysis also suggests that high-wage workers are paid more for the firm's success.[22]

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

[21] 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 endogeniety.

[22] For descriptions of forms of incentive pay for other knowledge workers, and models and empirical results, for the CEO literature, see Hallock and Murphy (1999), Gibbons and Murphy (1992), Jensen and Murphy (1990), and Murphy (1999).

Note that this should be interpreted as a firm-specific fixed effect: the firm that is highly productive in 1997 (when we measure the firm's revenues) pays more to workers in adjacent years as well.

In sum, the quantile regressions show that earnings are higher when firms operate in high variance product markets and that earnings are higher when firms succeed by achieving high revenues. Moreover, those workers at the upper end of the earnings distribution are rewarded disproportionately when firms operate in high variance product markets and when firms succeed by achieving high revenues. These results are robust when we look at different measures of income, and when we reduce the data set to only those individuals who are in software occupations.[23]

The Earnings Growth Rates for Software Workers

The main results on the impact of payoff potential are mimicked when we use within-job earnings growth, *Within-Job Earnings Growth*, as the dependent variable instead of the earnings level (columns 7 and 8). Within-job earnings growth rises sharply with the potential payoff of the firm, and this impact is greatest for the highest earnings quantiles.

In contrast, *Between-Job Earnings Growth* (columns 9 and 10) is not a function of the potential success of the firm: workers are rewarded for staying with the firm but not for hopping between firms. For the median worker, the effect of payoff potential for between-job earnings growth is actually negative, but at higher earnings quantiles, it is insignificant. Thus, even though starting salaries are higher for individuals working in high variance product classes (columns 3 and 4), firms in these high variance industries do not appear to be stealing stars from other firms by offering high starting salaries. Of course, we cannot observe whether firms are stealing stars by offering high stock option grants. But the point remains that even if they are, the stars must stay with the firm four or more years to have their options pay out, and the stars must succeed at what they are doing. Job hopping for higher future earnings may be a common strategy, but such job hopping is not a viable short term strategy for wage growth. In this sense, loyalty pays – workers must stay with firms to achieve income growth.

How Much Do High Payoff Firms Pay for Stars?

The results in Table 5 show that firms operating in high variance product classes pay higher wages. How much more do they pay, and to whom?

Table 6 shows the predicted value of earnings for alternative combinations of worker wage classes and firm product market classes. The five columns represent the three wage classes: starting salary for the typical median worker; starting salary for the worker at the 90^{th} wage percentile; experienced-worker salary for the median worker; the experienced-worker salary for the experienced worker in the 90^{th} wage percentile; and in the last column the annual earnings growth rates for median workers. The rows vary the product class across the extremes: the first row is firms in the lowest variance product class (the mainframe applications having a product

[23] When we reduce the sample to those with matched occupational data from the Decennial Census (see data descriptions section), we find the same basic results.

payoff dispersion of .55); the median product class (with a payoff dispersion of 1.00); and the high variance product class (of video games having a product payoff dispersion of 1.33). Thus, the middle row of the table anchors the earnings at the actual median values of our data. For example, the starting salary for the median worker is $58,000.

Table 6: Predicted Earnings and Earnings Growth from Table 5 Regressions

	Beginning of Spell Earnings "Starting Salaries"		*End of Spell Earnings "Experienced Earnings"*		*Within-Job Earnings Growth*
	Median	90th Percentile	Median	90th Percentile	Median
Low Product Payoff Dispersion (Database software: 90/50 Ratio =.55)	$54,394	$94,845 (12.76%)	$80,285	$195,047	9.51%
Median Product Payoff Dispersion (90/50 Ratio=1.00)	$58,000	$108,000	$95,000	$311,000	xxx
High Product Payoff Dispersion (Game/Entertainment Software: 90/50 Ratio 1.31)	$61,023	$118,184 (15.30%)	$107,581	$437,573	15.90%

The predicted values of Table 6 display two pronounced conclusions from our regressions. First, firms operating in high-risk product classes pay more for talent, even in starting salaries. For the typical median worker, starting salaries rise from $54,394 to $61,023 as we span from low to high product class dispersion. More important, for the high skilled worker in the 90th wage percentile, starting salaries rise from $94,845 to $118,184. Second, earnings growth is dramatically higher in firms operating in high dispersion product classes. Experienced workers earn much more in firms operating in higher variance product classes (looking at columns 3 and 4). The higher returns to experience arise because workers who stay with their firm have strikingly high earnings growth in high variance product classes (looking at column 5). The regressions in Table 5 showed that high variance firms do not reward job hopping, so we don't present simulated wages from the between job earnings growth regressions. The overall conclusion is that loyalty pays, and it pays the most for workers in firms in high variance product classes.

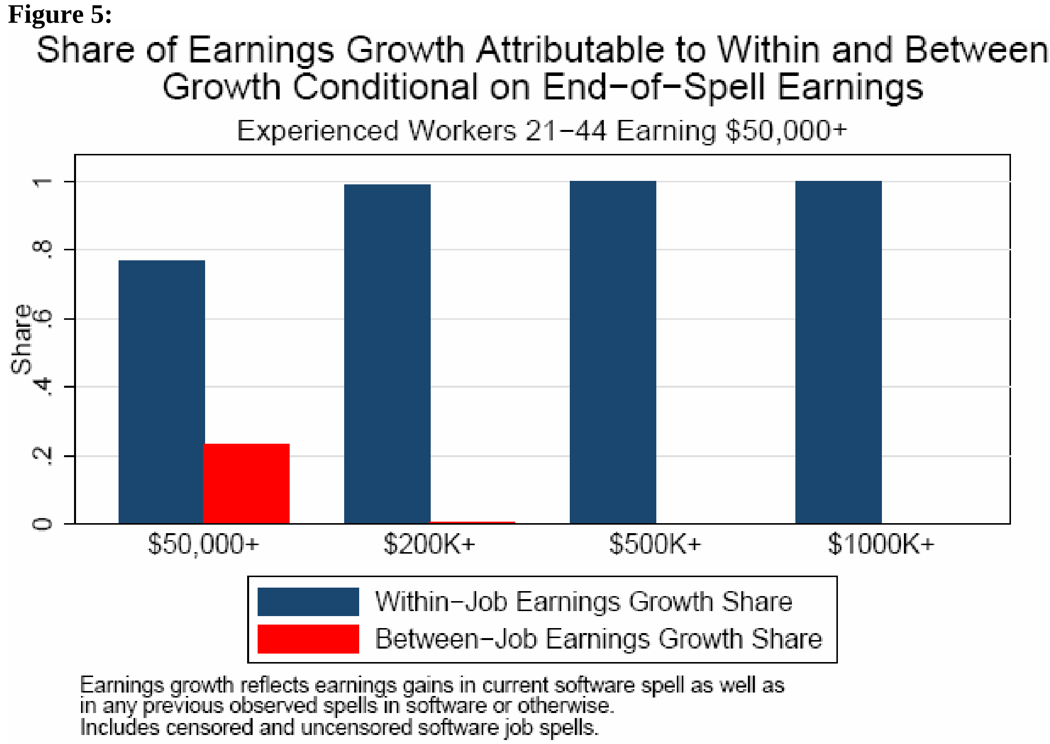
We use the phrase 'loyalty pays' to graphically counter the often heard phrase 'job hopping pays' to characterize software stars.[24] A typical perception of the software industry is that stars hop from firm to firm. We find that the typical worker is loyal and is rewarded for that loyalty with higher earnings: in other words, the typical worker stays at least five years, and workers with greater tenure boast much higher potential earnings than workers who hop between jobs. Moreover, the firms that reward such loyalty the most are the very firms that operate in high-risk (and thus high-payoff) product markets. We cannot assess why loyalty pays—it could be teamwork, the firm's protection of its intellectual property, or the long run development duration of projects—but it does pay.

We return finally to the raw data to lend support to our regression results that loyalty pays. Figure 5 divides the source of wage growth for workers into wage growth achieved by moving between jobs (or "job-hopping") versus wage growth achieved by staying with the same firm and

[24] See Fallick, Fleischman, and Rebitzer (2004) for results focusing on geographic variation in job hopping among software workers

experiencing pay increases (for the 'within' firm pay). For the approximately 4% of the sample who earn over $1 million in the last period in which we observe them, as we look back over their careers, over 95 percent of their wage growth arose within firms, and less than five percent from movement between firms.[25] By contrast, among software workers in the $50-75K range, the final pay is achieved by a combination of changing jobs and by wage growth when they stay within a firm and experience wage increases. See Appendix 3 for more analysis of wage growth as a function of the number of different employers.

Figure 5:



Thus, the striking result from Figure 5 is that even within the software industry, workers earn more from loyalty to their employer. That is, by far the greatest wage gains come not from hopping between employers, but rather from staying with an employer and earning higher pay over time. The figure corroborates our regression results: *high wage growth arises for workers in high payoff product markets when they stay with their current employer—for these workers, the return to loyalty can be very high.*

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[25] Our definition of between-firm wage growth is annualized starting compensation minus the ending compensation at the last firm. The starting compensation does not include options granted, so in some sense we could say that we are underestimating the gains to job hopping if software workers are moving between firms to achieve higher option grants. Nevertheless, our key point is that options granted are not yet compensation – the individual must stay with the firm four years (typically) to vest the options granted and the options must be "in-the-money" as a result of performance. Thus, even if options are granted with job change, the pay is only realized from within firm pay increases – the person must stay and perform.

The Selection of Stars

The point of the model is that highly talented workers should be sorted to firms operating in product markets that have high potential payoffs. We would like to test whether this is the case, and since firms and econometricians never have individual performance data, we use each worker's earnings history, which can span up to ten years, to categorize workers as "star" versus "non-star."[26] How should a star be defined? A star worker could be an individual with a history of high earnings growth or one who achieved a high level of wages. We choose to combine these two features – high earnings growth and high earnings levels – to define star workers. When we construct other definitions of stars, based on earnings growth or levels alone, the regression results are basically the same.[27] Keep in mind that we limited the sample to individuals aged 21-44, which corresponds to the age range in which stars are likely to be revealed in software.

We define star workers as follows. First we rank workers by earnings levels and take the top 25 percent of workers. We then rank that subsample by cumulative earnings growth rates and take the top 10 percent of all workers in the data.[28] Thus, of the total sample of 51,859 software workers earning more than $50,000 at the observed end of their spells, 5,185 are 'stars' and 46,674 are not stars. While these cutoffs are fairly arbitrary, again, the results below are robust to alternative definitions of stars. Note finally that in ranking workers based on their earnings, we do not use their actual earnings; rather, we use the earnings residual from a regression. We calculate residuals from regressions of earnings levels and of earnings growth rates on tenure in the job and industry, age, censoring dummies, and the interactions of these variables.[29] Our goal in using the regression residuals is to identify the star workers whose earnings levels or growth rates are abnormally high relative to all other workers of their age or tenure cohort, so we take the standard age and tenure effects out of earnings before calculating star status.

[26] The time periods of the data vary by state, but on average we have eight years of data for each person.

[27] We also defined stars as those who only have high earnings growth and as those who only have high earnings levels, and the results we report below are the same signs and significance levels. However, one refinement proves to be interesting and is consistent with wage regression results reported in Table 5 above. To shed light on how workers with high earnings growth achieve that growth, we divide the growth of earnings into two categories to create two definitions of stars: between-job-earnings-growth stars, are those workers whose earnings growth regression residual (for cumulative earnings growth across all jobs) is in the top 10% of the sample; within-job-earnings -growth stars, are those workers whose earnings growth regression residual within employers (based on cumulative earnings growth for all employment spells) is in the top 10% of the sample. These latter two definitions permit us to examine whether some types of firms are "star makers" (having a higher probability of having within-firm stars) and if other types of firms are "star takers" (having a higher probability of having between growth stars). In essence, the between-job- earnings -growth stars are those that achieve high earnings growth by hopping between employers. We find that the probability of being a between-job- earnings -growth star is not a function of the product payoff dispersion or of the revenue per worker. These results are not surprising since between-job earnings growth was not a function of these variables in Table 7 (columns 9 and 10).

[28] Cumulative within-job earnings growth refers to the total gain in log annualized earnings accumulated within jobs divided by the number of full quarters employed. Cumulative between-job earnings growth refers to the total gain in log annualized earnings accumulated due to job transitions divided by the number of full quarters not employed. Total wage growth is merely the sum of these two components, or the log annualized end-of-career earnings less log annualized beginning-of-career earnings, divided by the number of full quarters that we observe the worker in the data set.

[29] Details on these regression specifications and their results appear in Appendix 2.

To validate our definition of stars, and illuminate the features of the data, Figures 6 and 7 show earnings distributions for non-star and star workers. In our data, experienced software workers have been at their firm five or more years on average, and at that point, the mean earnings of a star is $398,655. However, the top 500 workers in our sample (or those above the 90th percentile of end-of-spell earnings among stars in Table 7) earn on average over $6 million in their last quarter (at an annualized rate). For the top ten percent of our sample who are designated stars, a large percent of their final pay is from exercised stock options or parting bonuses. The last column shows that earnings are substantially lower for stars when measured one year prior to exiting the firm. The 90th percentile of one-year prior earnings is over $800,000—still very sizable, but not sky-high.[30] In contrast, non-stars have very little difference in their earnings when they exit the data and one year prior to exiting. The greater skewness in the earnings distribution for stars relative to non-stars is very evident in the Figures 6 and 7, but this skewness is not driven entirely by bonuses and options, since the same high skewness for stars is also evident in the earnings for one-year prior to departure.

Figure 6:

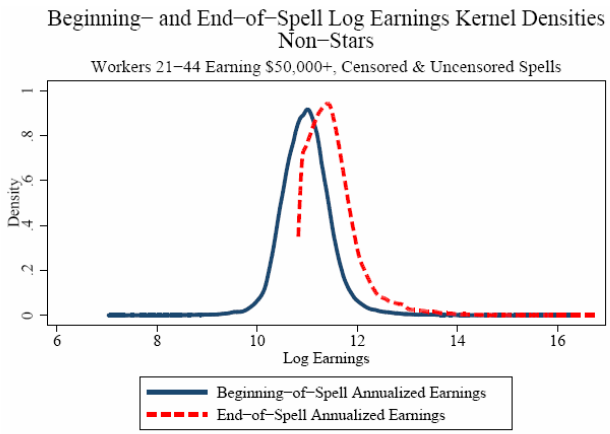

Figure 7:

[30] The proportion of spells that are right censored (so that our data ends before they exit from their job) varies by income level – from about 30% for workers with earnings between $50,000 and $75,000 to about 50% for workers in the higher income levels.

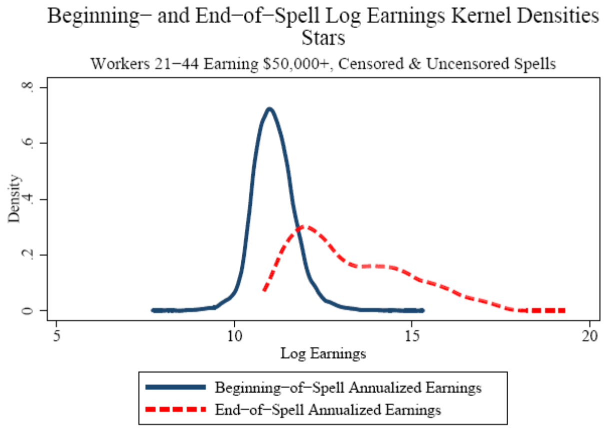

Table 7: Summary Measures of the Earnings Distribution of Star and Non-Star Workers

	Number of Observations	*Summary Statistic*	*Beginning of Spell Earnings "Starting Salaries"*	*End of Spell Earnings "Experienced Earnings"*	*One-Year Prior Earnings "Lagged Earnings"***
Non-Star	46,674	Mean	$68,270	$123,783	$163,588
		Median*	$57,991	$91,157	$84,896
		90th Percentile*	$104,609	$186,913	$191,338
		St. Dev.	$88,035	$244,017	$816,503
Star	5,185	Mean	$83,074	$2,329,019	$519,490
		Median*	$64,268	$398,655	$115,589
		90th Percentile*	$141,323	$6,527,895	$810,201
		St. Dev.	$104,172	$6,099,775	$2,454,469

* Average within a 10% band around the true percentile.

** Annualized earnings three quarters prior to last observed full quarter.

Using our designation of workers into star and non-star jobs, we estimate the probability that stars are located in high *Product Payoff Dispersion* firms. The main result is that being employed at a firm with a higher product payoff dispersion measure significantly increases the likelihood of being a star worker.[31] Our results in Table 8 imply that a worker employed at a game and entertainment software firm is eight percent more likely to be a star than a worker employed at a database software firm. The results vary by firm size. In simple regressions, with no controls, all firms that operate in high variance product markets have more stars. However, after addition controlling for firm age and job growth rate, only large firms have more stars in high payoff markets. Among small firms, actual success (or high revenue) increases the probability of hiring a star.

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[31] The positive and significant coefficient in the Product Payoff Dispersion variable is also significant for the occupation-matched sub samples for software engineers and software managers.

Table 8: Probit Regressions of the Probability of Being a Star Worker

Level+Growth Stars	*All Firms*					
	(1)	(2)	(3)	(4)	(5)	(6)
Product Payoff Dispersion +	0.1904	0.1671	0.1447	0.1541	0.1334	0.1075
	(0.0205)**	(0.0212)**	(0.0218)**	(0.0194)**	(0.0196)**	(0.0199)**
Log Revenue per Worker		0.0539	0.0577		0.0281	0.0301
		(0.0016)**	(0.0019)**		(0.0035)**	(0.0035)**
Firm Average Worker Churn			0.2741			0.3963
			(0.0689)**			(0.0687)**
Controls++	No	No	No	Yes	Yes	Yes
Observations	26276	26276	26276	26276	26276	26276
	Small Firms					
Product Payoff Dispersion +	0.0539	0.0422	0.0142	0.0371	0.0193	0.0081
	(0.0177)**	(0.0177)*	(0.0182)	(0.0158)*	(0.0156)	(0.0161)
Log Revenue per Worker		0.0180	0.0204		0.0212	0.0225
		(0.0037)**	(0.0037)**		(0.0034)**	(0.0034)**
Firm Average Worker Churn			0.3315			0.1560
			(0.0610)**			(0.0602)**
Controls++	No	No	No	Yes	Yes	Yes
Observations	7840	7840	7840	7840	7840	7840
	Large Firms					
Product Payoff Dispersion +	0.4973	0.5169	0.5092	0.2820	0.1805	0.2512
	(0.0411)**	(0.0452)**	(0.0457)**	(0.0511)**	(0.0541)**	(0.0561)**
Log Revenue per Worker		0.0698	0.0717		0.0384	0.0338
		(0.0027)**	(0.0032)**		(0.0067)**	(0.0068)**
Firm Average Worker Churn			0.1407			0.7437
			(0.1217)			(0.1511)**
Controls++	No	No	No	Yes	Yes	Yes
Observations	18436	18436	18436	18436	18436	18436

Standard errors in parentheses. * significant at 5%; ** significant at 1%. Marginal Effects are reported.
+ Weighted 90/50 Ratio of Log Revenue per Worker in Firm's Product Lines
++ Controls include (log) firm employment; (log) firm employment squared;
dummies for firm age (<6 years old, 6-10 years old, 11+ years old, with <6 omitted);
firm employment growth rate; a dummy for whether the firm is in a high density, high education,
and industrially diversified county; and year and quarter job separation dummies.

The Variance of Pay Within Firms

An interesting question remains: is the variance of earnings greater within firms operating in high variance product classes? Because we have earnings data on all individuals within all our firms, we are uniquely able to answer this question with the data.

There is no clear cut theoretical answer to the question. Consider the relationship:

(5) $\sigma^{W}{}_{jt} = \theta_0 + \theta_1(\sigma^{p}{}_{jt}) + \upsilon_{jt}$

where $\sigma^{W}{}_{jt}$ is the within firm variance in wages for firm j. In our data (and all other data sets) the earnings variance rises within firms with workers' tenure levels. The question is, is the variance of wages greater for firms in high variance payoff markets (a positive θ_1)? The answer depends on the nature of the production function within firms. Do firms that have a high payoff, σ^{p}_{jt}: a) want to employ only stars within the firm, so all are high paying with $\theta_1<0$ or $\theta_1=0$, or b) employ some stars than other firms have, so $\theta_1>0$? The theoretical answer depends upon the complementarity between stars and non-stars. In addition, if a substantial part of the compensation is group-based pay (as in bonuses), then $\theta_1<0$.

Our data provides the answer: for the most part, earnings inequality is greater within firms operating in high variance product classes. In Table 9, we use the individual earnings data, but with a dependent variable that is each worker's experienced earnings minus the median experienced earnings in his firm. The product payoff dispersion has a very strong positive effect (θ_1) on earnings inequality, and the effect grows with firm size. The rising effect with firm size is not surprising: it is well-known that executive pay rises with firm size, as CEO's in larger firms control more capital. What we show is that large firms operating in high payoff product markets have the highest within firm earnings inequality.

These results are largely replicated in Table 10, when the dependent variable is the 90/50 ratio of the earnings within the firm. The disadvantage of this approach is that the sample size decreases substantially when the unit of observation is the firm, for 688 firms, and thus we are losing the information on every person's position in the earnings distribution. The estimated θ_1 is significantly positive for starting salaries. For experienced earnings, the θ_1 is typically twice as large, but less precisely estimated. We do not detect firm size differences in θ_1 in this smaller data set. However, most notably, in the lower panel of Table 10, we show that when we take most stock options out of the data, the θ_1 remains positive.

Finally, consider how these results fit into the picture portrayed by our earlier earnings regression results. The earnings regression results presented in Table 5 provide an explanation for the increasing variance of wages over time across firms in the economy and within sectors and occupations: the increasing movement of the economy towards knowledge workers has increased the value of stars to firms, and thus increased the variance of pay. The variance of pay across all workers is rising due to the nature of the production function (the need for stars), and the sorting and rewarding of stars to high payoff firms. The within-firm regression results of Tables 9 and 10 show that the variance of within-firm earnings is also a function of the variance of the product market payoffs that firms face.

Table 9: Regressions of Individual Wage Levels minus Firm-specific Median Wages

	All Firms		*Small Firms*		*Large Firms*	
	(1)	(2)	(3)	(4)	(5)	(6)
Product Payoff Dispersion+	0.3738	0.2912	0.1405	0.1495	0.8989	0.4256
	(0.0385)**	(0.0388)**	(0.0440)**	(0.0430)**	(0.0731)**	(0.0972)**
Log Revenue per Worker	0.1071	0.0357	-0.0042	0.0010	0.1187	0.0634
	(0.0048)**	(0.0068)**	(0.0098)	(0.0103)	(0.0063)**	(0.0111)**
Firm Average Worker Churn	-0.3363	-0.6089	0.3485	-0.2093	-1.0988	-1.3821
	(0.1011)**	(0.1200)**	(0.1134)**	(0.1358)	(0.1811)**	(0.2729)**
Controls++	No	Yes	No	Yes	No	Yes
Observations	26276	26276	7840	7840	18436	18436

All dependent variables are wage residuals from regression controlling for age and tenure (see Appendix 2).
Standard errors in parentheses. * significant at 5%; ** significant at 1%.
+ Weighted 90/50 Ratio of Log Revenue per Worker in Firm's Product Lines
++ Controls include (log) firm employment; (log) firm employment squared;
dummies for firm age (<6 years old, 6-10 years old, 11+ years old, with <6 omitted);
firm employment growth rate; a dummy for whether the firm is in a high density, high education,
and industrially diversified county; and year and quarter job separation dummies.

Table 10: Within-Firm Earnings Residual Dispersion Regressions

	Beginning of Spell Earnings "Starting Salaries"		*End of Spell Earnings "Experienced Earnings"*		*One-Year Prior Earnings "Lagged Earnings"*	
	(1)	(2)	(3)	(4)	(5)	(6)
Product Payoff Dispersion +	0.3060	0.2985	0.7685	0.7178	0.5273	0.4582
	(0.1084)**	(0.0965)**	(0.5585)	(0.2705)**	(0.3133)	(0.1985)*
Log Sales per Worker	0.0707	0.0206	0.6225	0.1183	0.3006	0.1069
	(0.0235)**	(0.0287)	(0.1613)**	(0.0954)	(0.0725)**	(0.0579)
Firm Average Worker Churn	0.2521	0.6981	-1.5985	2.8754	0.9884	2.8380
	(0.7097)	(0.4461)	(4.1871)	(1.7730)	(2.1438)	(1.2434)*
Constant	-0.1704	-0.0426	-2.9961	-0.2612	-1.3989	-0.5440
	(0.1842)	(0.1876)	(1.0964)**	(0.6083)	(0.5538)*	(0.3848)
Controls++	No	Yes	No	Yes	No	Yes
Observations	688	688	688	688	688	688
R-squared	0.26	0.36	0.67	0.89	0.59	0.76

All dependent variables are wage residuals from regression controlling for age and tenure (see Appendix 2).
Standard errors in parentheses. * significant at 5%; ** significant at 1%.
+ Weighted 90/50 Ratio of Log Revenue per Worker in Firm's Product Lines
++ Controls include (log) firm employment; (log) firm employment squared;
dummies for firm age (<6 years old, 6-10 years old, 11+ years old, with <6 omitted);
firm employment growth rate; a dummy for whether the firm is in a high density, high education,
and industrially diversified county; and year and quarter job separation dummies.

5. Conclusion

Innovation in the U.S. economy is about employing and rewarding highly talented workers to produce new products. This paper makes a key connection between talent and firms in markets with risky product innovations – 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 star workers. Thus, firms in high variance product markets pay more up-front—in starting salaries—to attract and motivate star employees, because if these star workers produce home-run innovations, the firm's winnings will be huge. However, we also find these same firms pay highly for loyalty: employees that stay with a firm for five or more years have much higher earnings in firms with high variance product market payoffs. These striking effects are robust to the inclusion of a wide range of controls for both workers and firm characteristics. One key control is that we also show that in firms that have actually hit home runs, with high revenues, the rewards for star talent are even greater.

There may be many factors underlying the finding that loyalty is rewarded more in firms operating in risky product markets. In these firms, workers are likely to have firm-specific human capital, and also worker quality is identified slowly on the job. However, much of their human capital is likely to be product-specific (such as a knowledge of wireless software), not firm-specific. Thus, firms tie workers to their firms through deferred compensation – they offer options that become vested only after the employee is with the firm four years. And clearly the deferred compensation is performance pay – stock options pay off only if the firm performs. However, our model emphasizes that firms pay high wages to employees just to be in the game – to play in the market where there are potential big winners – whether the firm actually wins or not.

Though we are studying only the software industry, our results should generalize to other industries that utilize knowledge workers. We study software workers because we want to focus on one production function, and because we are uniquely able to develop a dataset that matches data on software workers to data on software firms. Software firms are also the firms in which the activities of knowledge workers can be directly tied to the performance of the firm, and in which the workers are doing basically the same thing within and across firms, so we can describe and model the production function for these workers. They are also the firms that are the most innovative, and thus have the greatest potential payoffs from star talent. However, all industries that value project development that pays off should pay high wages to attract the most talented employees. Moreover, within firms, the highly innovative product development teams are likely to be more highly paid than others, all else constant. Thus, within-firm returns to innovation may also create within-firm variance in pay or inequality in pay. In our empirical analysis, we find that firms with the greater payoff potential are the firms that have the highest within-firm pay variance (though that is not a necessary prediction of our model).

Overall, our results documenting a link between income variance and innovation are consistent with results in the literature on income inequality, skill demand, and economic growth. The income inequality literature has shown that there has been an increasing return to skills both within occupations and industries as well as across occupations and industries. But relevant skills are hard to define and measure – education and experience are inadequate measures of skills. Autor, Levy, and Murnane (2003) show that the jobs that have seen all the employment growth in the U.S. are those jobs in occupations that utilize workers' non-routine cognitive skills, as in software development. Our focus on software is to look precisely at the demand and pay variance of those 'knowledge' workers who are experiencing rising demand and contributing to rising income inequality. And by choosing to study the software industry, we are narrowing our focus to workers who have the same basic education levels and one basic production function that is the same across firms. Thus, the variance in pay reflects the variance in skills and effort and the variance in the values that different firms place on software workers skills. We show that different values placed on innovation increases income inequality (or pay variance), but we interpret this increasing income inequality as a positive force – it is the inducement to increase skills and effort among software workers.

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Appendix 1: Construction of the Data

Sample

The Longitudinal Employer Household Database links state level data on Unemployment Insurance earnings of all employees within firms to employer data from Census surveys (Abowd et al. 2004).[32] Since the scope of the LEHD data is virtually the full universe of employers and workers, movements of workers through the earnings distribution as well as across employers can be tracked accurately.[33] Because these data are administrative in nature, both the employment and earnings measures are different from those usually found in surveys. The information in each wage record is simply the total earnings for each individual in a given quarter with a given employer; there is no information on hours or weeks worked, or indeed the duration of employment within the quarter. One key advantage of this administrative data is that the earnings measures are quarterly and include bonuses and exercised stock options.[34]

For the analysis of compensation over workers' careers, we use a subset of ten states for which we have data for a sufficiently large number of years that we can construct worker earnings histories from which to make meaningful inferences. We also limit our data to workers between the ages 21 and 44, which permits us to focus on the demand for workers in the prime of their careers. We use earnings for individuals who where full-quarter employed in the final quarter of 1997 and whose dominant employer (i.e., the employer at which the worker earned the most in a given quarter) was in the software industry.[35] 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, which contains extensive information about businesses in the industry. We then construct complete employment and earnings histories for individuals in these firms, building backwards from their 1997 software spell and examining prior jobs, including those within the software industry and those in other industries.

These distributions helped to inform our decision to set the $50,000 (in $2001) threshold for our primary sample of workers.

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[32] As of November 2005, the LEHD had 40 partner states. This is an ongoing project and additional states are expected to join this program. Because of the sensitivity of these data it is worth noting that the data 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.

[33] Stevens' "Employment that is not covered by state unemployment insurance laws," LEHD TP 2002-16, describes coverage issues related to the LEHD database.

[34] 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 analysis of options granted and data available on option values, see Oyer and Schaeffer, 2004.

[35] Due to the inability to capture hours or weeks in the data, we use a full quarter (FQ) earnings measure. This measure represents earnings for workers who have been employed by the same employer for a full quarter; that is, it represents earnings for a worker who is observed 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.

Using firm identifiers on the UI data, we match LEHD data to the Economic Census. The Economic Census of the services industry is conducted by the U.S. Census Bureau in years ending in "2" and "7." We use the 1997 Economic Census because it characterizes the products produced by firms in the software industry at a level of detail greater than in any prior year. Unfortunately, products cannot be matched across Census years.

There were 83,497 job spells in software publishing that were ongoing in the fourth quarter of 1997 in the ten states in our sample.[36] When we condition on workers aged 21-44, the number of spells in the sample falls to 67,452. Finally, because we do not have occupational data in the full LEHD data set but would like to exclude administrative staff and other ancillary workers in the industry, we decide to limit our analysis to only spells that had annualized end-of-spell earnings greater than or equal to $50,000 (in $2001). This restriction, which limits the sample to 51,859 spells, is aimed at isolating computer programmers, developers, and managers while weeding out lower administrative and support staff. The $50,000 threshold was set in light the results of two separate, but related exercises. We first turned to the 5% Public-Use Microdata Sample (PUMS) from the 2000 Decennial Census to get a sense of the distribution of earnings within the relevant set of software occupations (programmers, developers, engineers, and managers in the software industry).[37] [38] We also matched our sample of workers with the Long-Form of the 2000 Decennial Census, which provided us with occupation information for slightly less than one-sixth of our sample. We then evaluated the earnings of those workers for whom we obtained occupational information. These exercises suggest that the $50K threshold is quite reasonable for focusing on software developers, engineers, and managers. We also note that for the core specifications we consider in the empirical analysis, we have estimated the specifications using the restricted matched sample where we directly observe occupation. In unreported results, we show that the main implications of the analysis are robust to the use of this restricted sample.

While most businesses in our $50,000+ sample of workers aged 21-44 could be successfully matched to the Economic Census, a smaller subset had complete information, including size, age, revenue, and detailed product line information. There are 26,276 spells for which we have complete information regarding worker characteristics as well as firm characteristics. All told, 688 firms are represented in this sample.

Measurement

The firm-specific potential payoff measure is computed as follows. Beginning with establishment-level Economic Census data, we distribute each establishment's total sales revenue across its product lines according to the reported percentages. We then aggregate to the EIN-product line level, summing sales across establishments within this EIN-product line. Next, we

[36] Counting the 1997 software spells and all the previous spells held by workers in these software jobs, we have 143,485 spells in the data.
[37] 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).
[38] We also use information from the Decennial to obtain information regarding basic characteristics of the counties in which people in the sample are employed, including population and employment densities, as well as average educational and income levels. These enter the control variables in the regressions.

aggregate to the EIN level since this is the common firm identifier in both the Economic Censuses and in the LEHD data. Total sales are summed by EIN, excluding the “other” product line categories. New percentages are then calculated (adjusted so they do not include "other" categories) at the EIN-product line level, and the payoff measure, which we calculate as the natural log of sales per worker, is distributed across all product lines within an EIN (after adjusting EIN total employment downward by the same percentage that total employer sales were adjusted downward due to the exclusion of the "other" categories). This number is the same across all product lines within an employer (we thus assume that profitability is the same across all product lines within an employer). Then, treating each EIN-product line combination as if it were its own establishment, we obtain the difference between 90th percentile and 50th percentile of log sales per worker by product line. Finally, these 90-50 ratios are merged back onto the EIN-product line file, and the weighted average of the 90-50 ratios associated with all the product lines within an employer is what is used as our measure of potential payoffs.

By using the 90/50 ratio, we focus on the upper tail of the payoff distribution. It is highly correlated with other measures of skewness. However, note that we do not have data on the lower tail of the distribution – we only observe positive revenue for the firms, not negative revenue – so we focus on the returns to high payoffs.

Appendix 2: Calculation of Residuals

Using the worker-spells data, we wish to characterize what it means to be a "star" worker – a worker whose wage level and/or wage growth rate is abnormally high. We do so by deriving residuals from regressions of earnings levels and growth rates; the purpose of using residuals is to find those individuals who have abnormally high earnings levels and/or earnings growth after controlling for their age and experience.

We begin by computing earnings level residuals for individuals in the sample. We compute the end-of-software-spell earnings level residual for each spell in the sample as the residual from a regression of log end-of-spell earnings on quadratics of tenure at job, tenure in industry, and age, fully interacted with each other and with appropriate left and right censoring dummies. In a similar fashion, we compute beginning-of-software-spell earnings level residuals and lagged end-of-software-spell earnings level residuals.

We then compute within job earnings growth residuals and between job earnings growth residuals for individuals in the sample. The former is the residual from a regression of within job earnings growth for each spell in the sample on quadratics of tenure at job and age, fully interacted with each other and with appropriate left and right censoring dummies. The latter is the residual from a regression of between job earnings growth for each transition on tenure at (previous) job and age, fully interacted with each other and with appropriate left and right censoring dummies as well as dummies for a switch within industry and a switch between industries. We then form an earnings growth residual for each individual that is simply the sum of within job and between job residuals over their work histories.

These residuals form the basis for our definitions of star software workers, of which we explored numerous in addition to those presented in this paper.

Table A1: Log End-of-Spell Annualized Earnings

Dependent Variable: Log End-of-Spell Annualized Earnings				
Observations	143,485			
Parameter	Estimate	Standard Error	t Value	Pr>|t|
Intercept	6.4046	0.0347	184.4000	<.0001
Tenure in Industry	0.0545	0.0039	14.1300	<.0001
Tenure in Industry Squared	-0.0010	0.0001	-12.0500	<.0001
Tenure in Job	0.0992	0.0040	25.0300	<.0001
Tenure in Job Squared	-0.0003	0.0001	-3.8800	0.0001
Age	0.1694	0.0017	97.5500	<.0001
Age Squared	-0.0016	0.0000	-75.0000	<.0001
Right Censored Spell	0.8766	0.0687	12.7600	<.0001
Left Censored Spell	-0.1425	0.0133	-10.7300	<.0001
Tenure in Industry x Left Censored Industry Spell	-0.0144	0.0039	-3.6800	0.0002
Tenure in Industry Squared x Left Censored Industry Spell	0.0002	0.0001	3.0300	0.0025
Tenure in Job x Left Censored Job Spell	-0.0187	0.0044	-4.2200	<.0001
Tenure in Job Squared x Left Censored Job Spell	0.0003	0.0001	3.1900	0.0014
Tenure in Industry x Right Censored Industry Spell	-0.0269	0.0219	-1.2200	0.2207
Tenure in Industry Squared x Right Censored Industry Spell	0.0003	0.0003	0.9000	0.3691
Tenure in Job x Right Censored Job Spell	-0.0418	0.0219	-1.9100	0.0564
Tenure in Job Squared x Right Censored Job Spell	0.0011	0.0003	3.2000	0.0014
Tenure in Industry x Age	-0.0004	0.0001	-4.1300	<.0001
Tenure in Job x Age	-0.0016	0.0001	-17.6900	<.0001
Tenure in Industry x Age x Left Censored Industry Spell	0.0004	0.0001	4.4600	<.0001
Tenure in Job x Age x Left Censored Job Spell	0.0002	0.0001	2.1300	0.0336
Tenure in Industry x Age x Right Censored Industry Spell	0.0001	0.0003	0.3600	0.7208
Tenure in Job x Age x Right Censored Job Spell	-0.0003	0.0003	-0.8600	0.3913
Separated Q1	0.0378	0.0072	5.2900	<.0001
Separated Q3	0.0595	0.0070	8.4700	<.0001
Separated Q4	0.0436	0.0074	5.8700	<.0001
Source	DF	Sum of Squares	Mean Square	F Value
Model	25	43,074.80	1,722.99	2,309.20
Error	143,459	107,040.92	0.7461	
Corrected Total	143,484	150,115.72		
R-Square	Coeff Var	Root MSE	LHS Variable Mean	
0.286944	7.844303	0.863796	11.01176	

Table A2: Log Beginning-of-Spell Annualized Earnings

Dependent Variable: Log Beginning-of-Spell Annualized Earnings				
Observations	143,485			
Parameter	Estimate	Standard Error	t Value	Pr>|t|
Intercept	6.8097	0.0257	265.3500	<.0001
Age	0.1829	0.0013	138.2700	<.0001
Age Squared	-0.0019	0.0000	-117.1200	<.0001
Left Censored Spell	-0.1313	0.0052	-25.0700	<.0001
Accessed Q1	-0.0862	0.0057	-15.1600	<.0001
Accessed Q3	0.0134	0.0054	2.4900	0.0128
Accessed Q4	-0.0296	0.0058	-5.0800	<.0001
Source	DF	Sum of Squares	Mean Square	F Value
Model	6	16,191.69	2,698.62	5,946.98
Error	143,478	65,107.30	0.45	
Corrected Total	143,484	81,298.99		
R-Square	Coeff Var	Root MSE	LHS Variable Mean	
0.199162	6.300298	0.673631	10.69205	

Table A3: Log Lagged End-of-Spell Annualized Earnings

Dependent Variable: Lagged Log End-of-Spell Annualized Earnings				
Observations	143,485			
Parameter	Estimate	Standard Error	t Value	Pr>|t|
Intercept	6.4128	0.0328	195.5500	<.0001
Tenure (Adjusted) in Industry	0.0313	0.0041	7.7200	<.0001
Tenure (Adjusted) in Industry Squared	-0.0005	0.0001	-4.7700	<.0001
Tenure (Adjusted) in Job	0.1602	0.0042	38.2400	<.0001
Tenure (Adjusted) in Job Squared	-0.0023	0.0001	-23.6400	<.0001
Age	0.1683	0.0017	99.9600	<.0001
Age Squared	-0.0017	0.0000	-77.8300	<.0001
Right Censored Spell	0.5539	0.0363	15.2400	<.0001
Left Censored Spell	0.0352	0.0085	4.1500	<.0001
Tenure (Adjusted) in Industry x Left Censored Industry Spell	0.0006	0.0045	0.1300	0.8958
Tenure (Adjusted) in Industry Squared x Left Censored Industry Spell	-0.0003	0.0001	-2.4100	0.0161
Tenure (Adjusted) in Job x Left Censored Job Spell	-0.0777	0.0048	-16.0300	<.0001
Tenure (Adjusted) in Job Squared x Left Censored Job Spell	0.0019	0.0001	17.0800	<.0001
Tenure (Adjusted) in Industry x Right Censored Industry Spell	-0.0367	0.0196	-1.8800	0.0606
Tenure (Adjusted) in Industry Squared x Right Censored Industry Spell	0.0009	0.0003	2.6300	0.0085
Tenure (Adjusted) in Job x Right Censored Job Spell	-0.0271	0.0197	-1.3800	0.1689
Tenure (Adjusted) in Job Squared x Right Censored Job Spell	0.0007	0.0003	2.1500	0.0314
Tenure (Adjusted) in Industry x Age	-0.0003	0.0001	-2.9200	0.0035
Tenure (Adjusted) in Job x Age	-0.0017	0.0001	-18.0700	<.0001
Tenure (Adjusted) in Industry x Age x Left Censored Industry Spell	0.0004	0.0001	3.8300	0.0001
Tenure (Adjusted) in Job x Age x Left Censored Job Spell	0.0005	0.0001	4.4300	<.0001
Tenure (Adjusted) in Industry x Age x Right Censored Industry Spell	-0.0003	0.0003	-1.0500	0.2947
Tenure (Adjusted) in Job x Age x Right Censored Job Spell	0.0003	0.0003	0.8100	0.4184
Quarter 1 Dummy	-0.0231	0.0070	-3.3100	0.0009
Quarter 2 Dummy	0.1038	0.0068	15.1600	<.0001
Quarter 4 Dummy	0.1318	0.0072	18.2100	<.0001
Source	DF	Sum of Squares	Mean Square	F Value
Model	25	53929.872	2157.1949	3041.4
Error	143459	101752.14	0.7093	
Corrected Total	143484	155682.01		
R-Square	Coeff Var	Root MSE	LHS Variable Mean	
0.34641	7.752834	0.842186	10.86294	

Table A4: Annualized Within-Job Earnings Growth

Dependent Variable: Annualized Within-Job Earnings Growth				
Observations	143,485			
Parameter	Estimate	Standard Error	t Value	Pr>|t|
Intercept	0.0877	0.0122	7.2200	<.0001
Tenure in Job	0.0143	0.0006	23.6300	<.0001
Tenure in Job Squared	-0.0002	0.0000	-12.6600	<.0001
Age	-0.0037	0.0006	-6.2100	<.0001
Age Squared	0.0000	0.0000	4.1400	<.0001
Right Censored Spell	0.3153	0.0234	13.4600	<.0001
Left Censored Spell	0.0097	0.0048	2.0100	0.0449
Tenure in Job x Left Censored Job Spell	-0.0039	0.0008	-4.7900	<.0001
Tenure in Job Squared x Left Censored Job Spell	0.0001	0.0000	4.5900	<.0001
Tenure in Job x Right Censored Job Spell	-0.0283	0.0019	-14.7000	<.0001
Tenure in Job Squared x Right Censored Job Spell	0.0005	0.0000	14.3900	<.0001
Tenure in Job x Age	-0.0001	0.0000	-9.1400	<.0001
Tenure in Job x Age x Left Censored Job Spell	0.0000	0.0000	0.4800	0.6339
Tenure in Job x Age x Right Censored Job Spell	0.0000	0.0000	0.9100	0.3627
Separated Q1	-0.0021	0.0025	-0.8300	0.4091
Separated Q3	0.0242	0.0025	9.8400	<.0001
Separated Q4	0.0263	0.0026	10.1200	<.0001
Accessed Q1	0.0153	0.0026	5.9800	<.0001
Accessed Q3	-0.0049	0.0024	-2.0200	0.0433
Accessed Q4	-0.0200	0.0026	-7.6000	<.0001
Source	DF	Sum of Squares	Mean Square	F Value
Model	19	310.60719	16.34775	179.97
Error	143,465	13,031.52	0.09083	
Corrected Total	143,484	13,342.13		
R-Square	Coeff Var	Root MSE	LHS Variable Mean	
0.02328	399.5266	0.301387	0.075436	

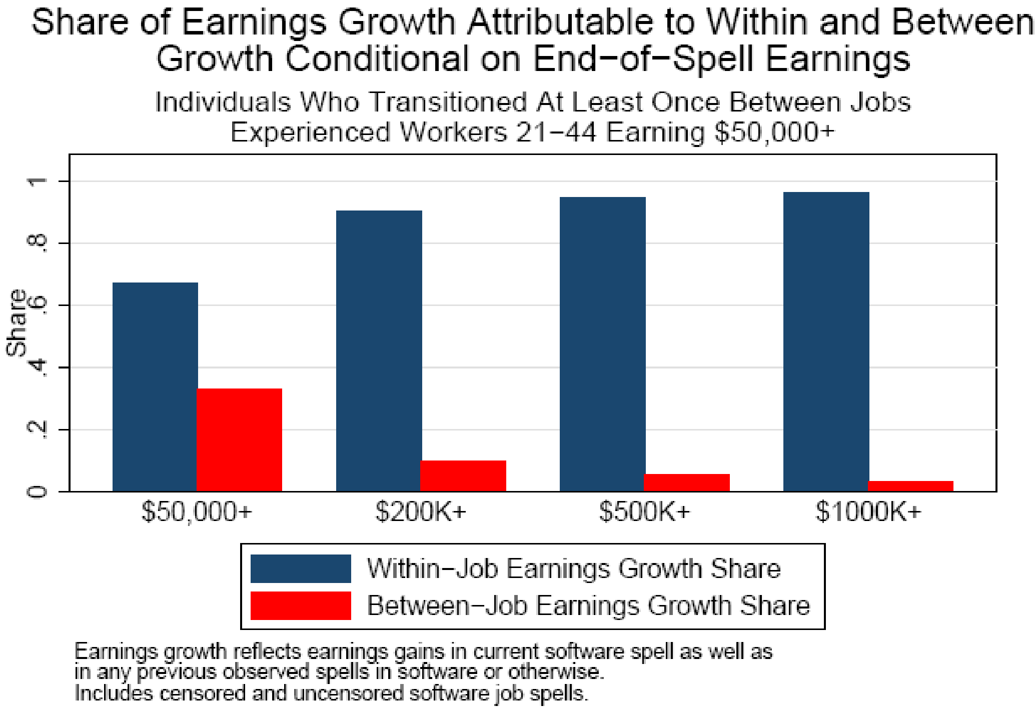
Table A5: Annualized Between-Job Earnings Growth

Dependent Variable: Annualized Between-Job Earnings Growth				
Observations	59,538			
Parameter	Estimate	Standard Error	t Value	Pr>|t|
Intercept	1.6536	0.0382	43.3100	<.0001
Age	-0.0588	0.0019	-30.4600	<.0001
Age Squared	0.0006	0.0000	23.6500	<.0001
Tenure in Previous Job	-0.0491	0.0045	-10.8900	<.0001
Tenure in Previous Job Squared	0.0016	0.0002	7.2700	<.0001
Left Censored Tenure in Previous Job	-0.1683	0.0130	-12.9400	<.0001
Tenure in Previous Job x Left Censored Previous Job Spell	0.0482	0.0054	8.9400	<.0001
Tenure in Previous Job Squared x Left Censored Previous Job Spell	-0.0012	0.0003	-4.2500	<.0001
Age x Tenure in Previous Job	0.0005	0.0001	4.8000	<.0001
Age x Tenure in Previous Job x Left Censored Previous Job Spell	-0.0007	0.0001	-7.1100	<.0001
Switch Within Industries	-0.1002	0.0068	-14.8200	<.0001
Switch Between Industries	(omitted)	.	.	.
Separated Q1	-0.0132	0.0073	-1.8000	0.0716
Separated Q3	-0.0038	0.0063	-0.6100	0.5427
Separated Q4	-0.0253	0.0078	-3.2400	0.0012
Accessed Q1	0.0051	0.0066	0.7700	0.4411
Accessed Q3	-0.0049	0.0064	-0.7600	0.4463
Accessed Q4	0.0712	0.0071	10.1000	<.0001
Source	DF	Sum of Squares	Mean Square	F Value
Model	16	1,581.45	98.84088	293.17
Error	59,521	20,066.95	0.33714	
Corrected Total	59,537	21,648.40		
R-Square	Coeff Var	Root MSE	LHS Variable Mean	
0.073052	294.0657	0.580638	0.197452	

Appendix 3:

As Figure 5 in Section 5 suggests, individuals with relatively high earnings levels who were in the midst of software spells in 1997 experienced much of their earnings growth through within-job earnings growth over the course of their entire employment histories including the software spell and prior spells. However, one might be suspicious of these results given that some spells may be censored and that those who are not observed to transition between jobs necessarily have shares attributable to within-job earnings growth equal to one. Yet, as Figure A1 reveals, even for those who are observed to transition at least once, the share of growth attributable to within-job earnings growth is substantially higher among the highest earners.

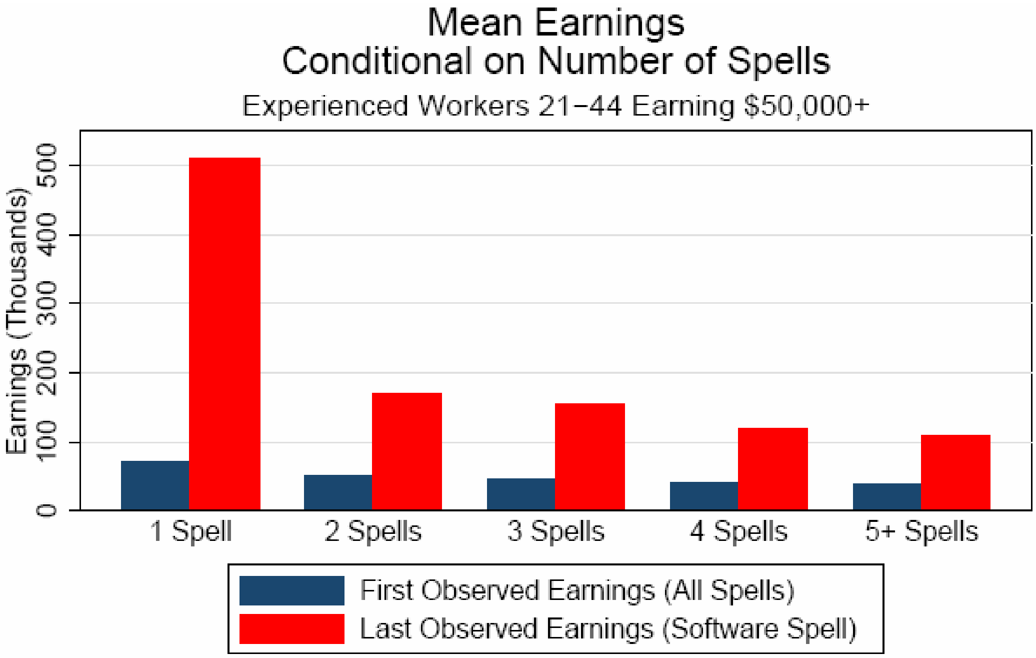
Figure A1:



The following two figures reinforce this message. They depict the share of earnings growth attributable to within-job earnings growth and between-job earnings growth by number of spells. While the share of earnings growth attributable to within-job earnings growth falls with the number of job transitions observed, those with the highest end-of-spell earnings tend to be individuals observed in relatively few spells.

Figure A2:

Figure A3:



Earnings growth reflects earnings gains in current software spell as well as in any previous observed spells in software or otherwise.
Includes censored and uncensored software job spells.