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OCCUPATIONAL EMPLOYMENT RISK AND ITS CONSEQUENCES FOR UNEMPLOYMENT DURATION AND WAGES

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Abstract

There are substantial differences in unemployment durations and reemployment outcomes for workers in different occupations. This paper shows that this variation can be explained in part by differences in occupational employment risk that arise from two sources: (1) the diversification of occupational employment across industries, and (2) the volatility of industry employment fluctuations, including sectoral comovements. The analysis combines data from the Quarterly Census of Employment and Wages with the National Longitudinal Survey of Youth 1979 male sample. Applying a competing risk duration model, this analysis finds that unemployed workers in high employment risk occupations have 5.2% lower hazard ratios of leaving unemployment to a job in the same occupation and have 4.9% higher wage losses upon reemployment than workers in low employment risk occupations. Among occupational switchers, workers in higher employment risk occupations have 11% higher wage losses than workers in lower employment risk occupations.

1. Introduction[1]

This paper documents substantial differences in unemployment durations and reemployment outcomes across workers in different occupations. It also argues that this variation comes in part from the fact that some occupations have a more diversified portfolio of employment choices than others. For instance, occupations common to many industries, like accountants, have a well-diversified portfolio of employment opportunities, while occupations common to only a handful of quite volatile industries, like earth drillers, have a much more concentrated portfolio of employment options.

Looking at the data, one can observe a large variation in average unemployment durations and wage losses across occupations (see Table 1 and Figure 1).[2] A striking aspect of these numbers is that differences in unemployment duration and wage losses are present even among closely related occupations with seemingly similar levels of skills, education, training, and work performed. For instance, there are large differences in duration and wage outcomes both among low-skill blue-collar occupations (e.g.,between “fabricators and assemblers” and “handlers and laborers”) and among high-skill white-collar occupations (e.g., “engineering and science technicians” and “other technicians”). This suggests that variation in workers’ characteristics alone, especially in educational attainment, cannot explain why individuals in some occupations face longer unemployment spells and greater wage losses than individuals in other closely related occupations. Figure 2 presents

[1] I would like to thank John Rust, Seth Sanders, John Shea, Bill Evans, Mark Duggan, Jeffrey Smith, Judith Hellerstein, Audrey Light, Jay Zagorsky, Steve McClaskie, Alex Whalley, and Juan Contreras for invaluable comments and suggestions.

[2] These averages are reported for 45 detailed occupational codes, an intermediate occupational classification (between two- and three-digit codes), established by the Current Population Survey (CPS).

occupational differences in average wage change upon reemployment for occupational stayers and occupational switchers.[3] We can see from this figure that wage loss variation is present regardless of whether workers switch occupations or not upon reemployment.[4]

Past studies of unemployment duration and wage determination have acknowledged the relevance of an individual's occupation by differentiating workers either between blue- and white-collar occupations or by their main occupational groups. However, only recently have studies tried to investigate why occupations are important to employment and wages. For a long time, economists have considered firm-specific skills to play a major role in earnings determination.[5] Conflicting findings regarding the magnitude of tenure effects on earnings profile led Neal (1995) and later Parent (2000) to examine whether industry-specific human capital is more important in explaining earnings than firm-accumulated skills. Both studies find evidence in favor of industry-specific skills.

Most recently, a growing line of work has emphasized occupation rather than industry as the level of human capital specificity that is relevant to earnings. Kambourov and Manovskii (2002) and Poletaev and Robinson (2003 and 2004) show that the evidence for industry-specific capital is weak and that the data are consistent with a more general skill measure of human capital, like occupation. They find that when occupation or a set of skills specific to an occupation is taken into account, industry and firm-specific human capital lose

[3]Occupational stayers are workers reemployed in the same occupation they held in their previous job, while occupational switchers are those that change occupation upon reemployment.

[4]I also examined whether this observed variation on wage losses was due to an uneven distribution of displaced workers across occupations, since they may suffer greater wage losses upon reemployment than non-displaced workers. However, even for displaced workers I still find the same large variation, whether or not they switched occupations upon reemployment. Displaced workers are those that report losing their jobs due to layoff or plant closing.

[5]See Abraham and Faber (1987), Altonji and Shakotko (1987), and Topel (1991). For a complete discussion of the literature see Willis (1986).

their importance in explaining earnings. Their results suggest occupation captures an important component of human capital that is relevant for earnings determination.[6] Thus unemployed workers have an incentive to look for a job in the occupation they held previously so that they can retain and therefore capitalize on their occupation-specific human capital.

Another aspect of human capital that has attracted attention in recent years is the labor income risk associated with different skills. It has become common in the literature to assume that individuals with different skills or levels of accumulated human capital face different labor income risk.[7] In this paper, however, I show that there is another aspect of human capital risk that has not been studied and that seems to have an important role in explaining observable differences in unemployment duration and wage losses across occupations. In particular, I analyze differences in the diversification of employment opportunities faced by each occupation. I argue that differences in this risk arise from the large variation in the distribution of occupational employment across industries and from the fact that industries have different employment volatilities.

The combination of these two facts implies that some occupations have a more diversified portfolio of employment opportunities than others. This suggests that individuals employed in more diversified occupations potentially face lower unemployment risk than those in occupations with lower diversification, and may thus experience shorter

[6]Occupations are, in general, classified based on an exclusive set of specific skills and skill demands that uniquely define them. Among this set of specific skills are the nature of work performed, education, training, and work credentials.

[7]Most studies measure human capital risk as differences in the variance of labor income associated with different levels of skills. See, for example, Grossmann (2005) and Huggett, Yaron, and Ventura (2005).

unemployment spells and/or lower wage losses upon reemployment. I call this phenomenon occupational employment risk (OER).

Regarding the distribution of occupational employment, occupations can differ both in the number of different industries that employ them[8] and in their concentration across these industries. Looking at the data, one can see that there is a quite large variation in the number of industries that employ different occupations (see column 1, Table 2). For instance, in the 1990 Census data “accountants” are employed by 157 out of 158 three-digit industries, while “earth drillers” are employed by only 13 of these industries (see Figure 3).[9]

In addition, occupations vary enormously in the concentration of their employment across industries. It is not uncommon to see occupations with more than 75% of their employment concentrated in one or two industries, regardless of how many industries employ the occupation. These differences in occupational employment concentration across industries can be well summarized by a Herfindahl index of employment concentration.[10] Table 2 presents the Herfindahl index for each occupation. Similar to unemployment duration and wage loss, there is large variation in the concentration of occupational employment across industries. Some occupations, like “handlers and laborers” and those in “financial records”, have very low Herfindahl values and therefore low industry employment concentration, while occupations like “teachers” and “construction laborers” are highly concentrated in a few industries. Figure 4 graphs the Herfindahl values for all occupations

[8] In a sense this captures how transferable occupational skills are across industries.

[9] Appendix A.2 provides details on occupational and industry codes.

[10] A Herfindahl index of employment concentration can be obtained for each occupation by summing, across all industries, the squared shares of the occupation’s employment in each industry. This index is bounded between 0 and 1; the higher its value, the more concentrated across industries the occupational employment.

shown in Table 2. Even within major occupational groups, there is large variation in the concentration of occupational employment (see, for example, the difference between "teachers" and "engineers").

Aside from differences in the distribution of occupational employment, variation in industries' employment fluctuations is also important to occupational employment opportunities and should be taken into account when studying occupational employment risk. Given the uneven distribution of occupational employment across industries, differences in industries' employment fluctuations[11] can greatly affect the portfolio of employment opportunities faced by each occupation. Returning to the case illustrated by Figure 3, both "accountants" and "earth drillers" are employed by the construction industry, which is highly volatile. We can see from the figure that more than 80% of "earth drillers" are employed by the construction sector and that only a few other industries employ them. Among those are "metal mining", "nonmetal mining", and "cement, concrete, and plaster products", all of which are very volatile and exhibit strong temporal comovement with construction. So if the construction sector is hit by an idiosyncratic shock and lays off many workers, including "earth drillers" and "accountants", "earth drillers" would probably have a harder time finding a new job in the same occupation, since the construction industry is their main employer, and the other industries that employ them are probably comoving with construction (being affected by the same shock). Unemployed earth drillers can change occupation in order to shorten their unemployment spell; however, we know from Kambourov and Manovskii (2002) and Poletaev and Robinson (2003 and 2004) that if they do so they are likely to have a

[11] Some industries face more frequent and/or larger shocks than others. For example, low aggregate demand or high oil prices can affect some industries more heavily than others. Sectors like construction, transportation, and services, for instance, are usually more volatile than other sectors.

higher wage loss, since they lose their occupation-specific human capital. Accountants, however, can more easily leave the construction sector and look for an accountant job in a different industry. In fact, only 5.2% of accountants are employed in construction and they can work for any other industry in the economy, many of which will not be comoving with construction.

In this paper, I combine the specific- human capital preservation motive with employment risk variation to explain differences in unemployment duration and wage losses across occupations. In order to do so, I define a measure of occupational employment risk, which I estimate using data from the Quarterly Census of Employment and Wages, years 1979-2000. I then relate this measure to unemployment duration and wage loss using a constructed weekly panel of employment and demographic histories for 5,579 males in the National Longitudinal Survey of Youth 1979 (NLSY79), which includes employer characteristics for up to five jobs each individual held during any year in the period 1979-2000. I find, as expected, that workers in high-risk occupations, as defined by the OER measure, have lower hazard ratios of leaving unemployment to a job in the same occupation and have higher wage losses than workers in low-risk OER occupations, especially if they switch occupations.

The paper is divided into five sections. Section 2 discusses the methodology used in order to measure occupation employment risk. Section 3 estimates the effect of OER on unemployment duration, while Section 4 relates this risk measure to wage losses. Section 5 presents conclusions and suggestions for future work.

2. Measuring Occupational Employment Risk (OER)

In this section, I define and construct a measure that depends both on the diversification of occupational employment across industries and on the level of industry employment volatility, including comovements. The employment opportunities of an occupation can be seen as a portfolio of industries where the weights are the shares of occupational employment in each industry and the rates of return are the industry volatilities.

To my knowledge, this study is the first to define and calculate a measure of employment risk associated with particular occupations, although a number of studies have estimated either the risk associated with aggregate employment volatility or different industries' unemployment risk. Neumann and Topel (1991) measure unemployment risk for workers in a particular locality as the variance of the within-market local demand uncertainty, $e'V$, where e is the vector of local industry employment shares and V the vector of estimated sectoral local employment shocks. Based on the assumption that workers are mobile within local markets,[12] they show that the sectoral composition of the market forms an implicit "portfolio of employment opportunities in which less specialized markets may achieve lower unemployment." The authors find that their measure explains differences in unemployment rates among geographically distinct labor markets.[13] Through the use of a similar measure, Shea (2002) finds that interindustry comovement is responsible for 95% of the variance of manufacturing employment.[14] Using 126 three-digit U.S. manufacturing industries over the

[12] Their argument is based on the assumption that if there are many goods and if skills are transferable, workers are mobile within local markets.

[13] In addition, they show that within-market changes in demand uncertainty had positive but only minor effects on within-market changes in unemployment.

[14] Shea estimates that the average pairwise correlation of annual employment growth is 0.34 and that, even after aggregating industries to 20 two-digit industry codes, comovement is still responsible for over 86% of

period 1959-1986, he estimates aggregate employment risk by decomposing annual employment growth into an average of industry growth rates, weighted by the industries' share of employment.

My idea builds on the fact that occupational employment is distributed unevenly across industries: some occupations are employed in many industries, while others are employed in only a small number of industries. Furthermore, different industries have different cyclicalities. In this context, it is reasonable to expect that different occupations may have diverse levels of employment risk associated with them. Occupations common to a larger number of industries may face a lower employment risk given that they have more diversified employment opportunities. In order to examine whether this is really the case, I construct a measure of occupational employment risk (OER) that considers two important dimensions of risk: the concentration of occupational employment across industries and the volatility and comovement of disaggregated industry employment. The OER measure is calculated in a fashion similar to the calculations of Neumann/Topel and Shea.

The concentration component of the OER measure is obtained by calculating the shares of occupational employment in each industry. S_{vj} is the share of occupation v in industry j, defined as follows:

$$S_{vj} = \frac{emp_{vj}}{emp_{v}}, \tag{1}$$

where emp_{vj} is the employment of occupation v in industry j and emp_{v} is the total employment in occupation v. I assume the shares to be in steady-state and compute them

manufacturing employment variation. For more on comovements, see Long and Plosser (1983) and Horvath (1998).

from the 1990 Census Public Use Microdata Series (PUMS) by constructing an occupation-by-industry employment matrix. I must make a steady-state assumption due to the lack of annual data on occupational employment by industry for the time period I consider. The limitation of making such an assumption is that if the occupational employment shares change significantly over time, my measure of OER will not capture these trends.[15] However, given that I am using a more aggregated occupational classification, these shares should be more robust to changes over time. Nevertheless, as a robustness check, I also estimated a version of OER using 1980 Census shares and obtained similar results.[16] I use 1990 shares since 1990 is the midpoint of my analysis.

The volatility component, Ω_ε, is constructed using the variance-covariance matrix of disaggregated industry employment growth rates, $\varepsilon_{jt},\ j = 1,...J$, and $t = 1978,...2000$, which I estimate using data from the Quarterly Census of Employment and Wages (QCEW) over the period 1978 to 2000.[17] In particular, note that Ω_ε incorporates not only the variance of industry employment but also comovements among industries.[18] The QCEW contains information on the number of establishments, employment, and total wages of employees covered by various unemployment insurance programs. A nice feature of this data set is that it provides industry employment data for every four-digit industry at national, state,

[15]Note that the steady-state assumption of the shares of occupational employment in each industry is consistent with the well-known phenomenon of skill upgrading within industries, as long as all industries are shedding less-skilled workers at the same rate.

[16]The overall correlation of the shares of occupational employment in each industry between 1980 and 1990 is 0.98. Calculating this correlation separately for each occupation, I find the lowest correlation to be quite high (0.79 for "personal services occupations").

[17]Specifically, $\varepsilon_{jt}=\Delta log(emp_{jt})$.

[18]I have tried different specifications for estimating Ω_ε. In particular, using industry employment shocks estimated by controlling for industry-specific characteristics with and without year dummies, I obtain similar results, regardless of the specification I use, so I opted for the simplest specification.

metropolitan statistical area (MSA), and county levels for the period 1975-2004.[19] The main limitation, however, is the change in industry codes over the time period (years 1975-1987 use the 1972 SIC, 1988-2000 use the 1987 SIC, and 1990-2004 use the NAICS). I deal with this issue by matching industry codes between the first two time periods in order to make the industry classification consistent for 1978-2000. The criterion I used was to merge 3-digit industry codes if one or more of their 4-digit industries are reported to be combined. Details about the industry code matching are in the appendix.[20]

I next assume that the growth rate of employment for a particular occupation can be (first-order) approximated as a weighted average of industry employment growth rates, where the weights are the shares of occupational employment in each industry:[21]

$$OEG_{vt} \cong \sum_{j=1}^{J} (S_{vj} * \varepsilon_{jt}), \qquad v = 1, ..., V; \quad j = 1, ..., J, \tag{2}$$

where J is the number of industries, V is the number of occupations, and OEG_{vt} is a first-order approximation of the growth rate of employment in occupation v at time t.

My benchmark measure of occupational risk is calculated as the implied variance of the (unobserved) growth rate of occupational employment:

$$OER_v = Var(OEG_{vt}) = S_{vj} \Omega_{\varepsilon} S'_{vj}, \tag{3}$$

[19] Data for certain establishments under government ownership are not disclosed, so the total employment in these industries will be somewhat underestimated.

[20] For an extensive discussion of the criteria applied and the constructed crosswalk, see Tristao (2005).

[21] This assumption, however, would not be robust to de-skilling, even if de-skilling was uniform across industries.

where S_{vj} is a $1 \times J$ vector of occupation $v's$ industry shares and Ω_ε is a $J \times J$ matrix of variances and covariances of $j's$ employment growth rates. It is worth noting that this measure has a lower bound at zero but is unbounded from above.

The OER measure is estimated for 158 3-digit industry codes and 45 “detailed” occupational codes, an intermediate occupational classification (between two- and three-digit codes), given by the Current Population Survey (CPS).[22] There are two main advantages to using this classification of occupations. The first is that workers may consider their skills to fit more than one three-digit occupation, which could lead them to search for a job in a closely related occupation. For example, a worker whose three-digit occupation is “payroll and timekeeping clerk” may also apply for “billing Clerk” jobs.[23] Second, a more aggregate classification reduces the problem of measurement errors from occupational misclassifications, which is an issue in other longitudinal studies using occupations.[24] Nevertheless, the CPS detailed occupational codes is still quite a rich classification, with three times as many occupational categories as the two-digit code.

Figure 5 presents the OER measure for different occupations. One can see that there is a large variation in this measure of employment risk across occupations, even within closely related occupational groups. In the next two sections, I relate this measure to unemployment duration and wage loss in order to examine whether workers in higher employment risk occupations indeed face longer unemployment spells and wage losses than workers in lower

[22]See Appendix A.2 for a description.

[23]These two occupations are classified as being closely related by the Occupational Outlook Handbook published by the Bureau of Labor Statistics (BLS).

[24]See Kambourov and Manovskii (2002 and 2005) and Neal (1995) for discussions.

employment risk occupations.[25]

3. OER Measure and Unemployment Duration

In this section, I estimate the effect of OER on the hazard rate of leaving unemployment and, consequently, on the length of unemployment spells. In light of recent evidence showing the relevance of occupation-specific human capital to earnings, unemployed workers have an incentive to look for a job in the occupation they held previously, so they can retain and therefore capitalize on their occupation-specific human capital. This suggests that it is important to distinguish between two exit modes from unemployment: finding a job either in the same or in a different occupation. In order to take these two exits into account, I use a continuous-time competing risk model, which I estimate by using a Cox proportional hazards model with multiple spells and time-varying covariates.[26] It is worth noticing that this procedure also takes into account the order in which these unemployment spells occur.

The main reason for choosing this specific regression model is that it allows me to estimate the relationship between the hazard rate and explanatory variables without imposing any parametric assumption about the shape of the baseline hazard function, $h_0(t)$.[27] Not having to parameterize $h_0(t)$ is desirable in this context because it eliminates the need to make assumptions on how the hazard changes over time. Incorrect assumptions on the shape of $h_0(t)$ would produce incorrect results regarding how the covariates affect the hazard. The

[25] The correlations between the OER measure and the average unemployment duration and wage loss are 0.18 and -0.16, respectively.

[26] See Jenkins (2004), chapter 8.

[27] Cox (1972) proposes a method for estimating the covariates without having to make any assumptions about the shape of the baseline hazard function, which in fact is not even estimated. This method relies on the assumption of proportional hazard and is estimated by partial likelihood rather than maximum likelihood.

only assumption made concerning the shape of $h_0(t)$ is that it is the same for everyone.[28] The Cox model is often called semiparametric because the effect of the covariates is parameterized and is assumed to shift the baseline hazard function multiplicatively. The hazard rate for the *i*th subject in the data is:

$$h(t/x_i(t)) = h_0(t)e^{(x_i(t)\beta_x)}, \tag{4}$$

The baseline hazard can be estimated separately, conditional on the estimates of β_x. I specify the relative hazard to be:

$$e^{(x_i(t)\beta_x)} = exp(\beta_1 OER_v + \beta_x X_i(t) + \beta_z Z_i(t)) \tag{5}$$

where OER_v is the occupational employment risk measure for occupation v. X_{it} is a vector of demographic characteristics that include age, measures of ability, a dummy for race, marital status, and educational attainment. The measures of ability are the first two principal components of the age-adjusted Armed Services Vocational Aptitude Battery (ASVAB) scores,[29] obtained by following the two-step methodology presented by Cawley et al. (1995) and Kermit et al. (2005). The appendix provides details. $Z_i(t)$ is a vector containing relevant work history information, including years of work experience and tenure in the previous job, a dummy for receiving unemployment compensation during the unemployment spell, and the local unemployment rate.[30]

[28] See Kalbfleisch and Prentice (2002) for a rigorous treatment and Cleves et al. (2004) for an intuitive discussion.

[29] The ASVAB is a set of ten tests measuring knowledge and skill in different areas.

[30] In order to capture nonlinear effects, I also include quadratic terms for age, ability, experience, and tenure.

3.1 Construction of the Panel

The data set I use to assess the relevance of the OER measure for unemployment duration and wages is the National Longitudinal Survey of Youth 1979 (NLSY79). The NLSY79 is a nationally representative sample of 12,686 young men and women who were 14-22 years old when they were first surveyed in 1979. Detailed information on these individuals' demographic characteristics and labor force participation has been collected since 1979.[31] This paper uses the unbalanced panel of civilian males, covering 1979-2000, which contains 5,579 individuals.[32]

I restrict the sample to individuals who were at least 21 years old at the beginning of an unemployment spell. In order to exclude possibly discouraged workers, in the unemployment duration analysis, I further restrict the sample to unemployment spells whose duration were less than 53 weeks. Furthermore, I consider only "completed" spells, which I define as a transition from employment to unemployment and then back to employment again, except for the last spell in the sample, which may be censored.[33] The duration of a spell is the difference in weeks between the beginning and the end of the spell.

Relative to other micro data sets, the NLSY79 has two distinct features that make it the best data to answer my particular question. First, the NLSY79 work history data are available on a weekly basis. Since a significant number of unemployment spells are very short, this high frequency is quite important.

[31] Data were collected annually from 1979 to 1993, and biennially from 1994 to the present.

[32] I restrict the sample to males in order to avoid labor force participation issues that arise when including women in the sample.

[33] A worker is considered unemployed by the NLSY if he or she did not work at all during the survey week and is currently searching or has searched for a job in the four weeks prior to the survey.

Second, and most importantly, the NLSY79 is one of few data sets that provides a complete work history for a specific cohort, which allows researchers to analyze completed unemployment spells.[34] This is one of the most desirable attributes of a data set for studying labor force transitions and unemployment duration, and it constitutes a significant advantage of the NLSY79 over the Current Population Survey (CPS) data, where unemployment spells are incomplete and cohorts change over time. Most studies analyzing unemployment duration in the United States use CPS data on spells in progress. Based on the steady-state assumption that flows in and out of unemployment are constant over time, existing studies estimate either the expected length of spell duration for a synthetic cohort of individuals entering unemployment (using continuation rates) or the average completed spell length for the currently unemployed workers (by "doubling" the average duration of their spells).[35] However, when steady-state conditions do not hold, both estimators can be biased. Rising unemployment will cause the steady-state method to underestimate completed spell lengths, while decreasing unemployment will cause this method to overestimate the length of spells.[36] In addition to the advantages mentioned above, the NLSY79 also has ability measures and has lower attrition rates than other longitudinal data sets (such as the Panel Study of Income Dynamics, or PSID). The downside of using the NLSY79 instead of the CPS is that I am able to analyze only individuals of a specific cohort that is still relatively young—in 2000, the individuals' age range was 35 to 43 years old.

[34]It is possible for the NLSY to construct a complete work history for each respondent, regardless of period of noninterview, because its survey questions are designed to recover the start and end dates for each labor force status change since the date of the last interview. See Appendix A.1 for details.

[35]For some of the most recent and influential papers using the CPS data see Darby et al. (1997), Baker (1992), Shimer and Abraham (2002), and Shimer (2005). Some exceptions are Dynarski and Sheffrin (1986 and 1990) using the PSID.

[36]For studies discussing the technical difficulties in measuring completed spells see Sider (1985) and Kiefer et al. (1985).

The NLSY79 collects detailed information on new and previously reported employers for whom a respondent has worked since the date of last interview. For every survey year, it reports up to five employers.[37] Using start and end dates of employment, as well as the job number assigned to each employer in every survey round (which can vary across rounds), I linked all employers across survey years as well as to the weekly work history files.[38] This allowed me to merge employer and job characteristics, such as industry and occupational codes, with the work history file. I also merge employees' main demographic characteristics, creating a weekly panel of employment and demographic histories for up to five jobs each individual held during any year in the period 1979-2000. For individuals with more than one job at a time, I consider the primary (CPS) employer as their main job. This panel allows me to obtain good measures of work experience and tenure with a given employer, which I calculate weekly by accumulating the number of weeks reported both working and working for a particular employer, respectively.

Issues that normally arise with the use of occupational codes (and to a lesser extent industry codes) are (i) individuals doing the same job can be coded as having different occupations and (ii) the same individual working in the same occupation can be coded differently across survey rounds, generating spurious occupational mobility. As I mentioned in the last section, in order to minimize measurement errors from misclassifications of occupational descriptions, I use a more aggregated occupational classification, which

[37] In fact, the NLSY79 collects information for all employers for whom a respondent has worked since the date of last interview. According to the NLSY documentation files, however, the number of respondents who report more than five jobs in each survey is less than 1% of those interviewed.

[38] Since employers can receive different job numbers across years, it is necessary to use beginning and ending dates as well as a series of other supporting variables that jointly taken indicate for every current survey employer the job number it received in the previous survey and whether it is a new job.

combines closely related occupations but still contains three times as many occupational categories as the two-digit code. Taking advantage of my panel of individual work histories within each employer, I eliminate the second type of problem by defining the occupation in each job to be the modal value of occupational codes ever reported for that employer, instead of the code reported in every survey round for that job. This is a significant improvement over previous studies that have used reported occupation codes in the NLSY79,[39] provided that one accepts the assumption that there is no genuine occupational change for individuals working for a given employer. A similar procedure was applied to industry codes.[40]

Table 3 shows the basic characteristics of the sample. The last two columns present the statistics conditional on remaining in the same occupation and switching occupation upon reemployment, respectively.[41] One can see from this table that around 44% of completed unemployment spells end in occupational mobility and that a larger fraction of workers who remained in the same occupation are white, single, have more experience and tenure, and report having used unemployment insurance. In comparison to workers who remained in the same occupation, more occupational switchers have a college degree and report having been displaced.[42]

[39] Neal (1999) assumes each employer's industry and occupational codes to be the first ever reported.

[40] For the NLSY79 civilian male sample, I estimate a significant amount of within-employer 3-digit occupation and industry miscoding over time. In fact, 88.9% of within-employer 3-digit occupational code changes and 88.4% of within-employer 3-digit industry changes are spurious, transitory changes. Genuine within-employer changes represent, respectively, only 6.66% and 7.92% of true occupational and industry mobility at the 3-digit level.

[41] Spells for which no occupational code was reported either for the previous job or the new job, or both, are omitted.

[42] Displaced workers are those that report losing their job due to layoff or plant closing.

3.2 Results

Table 4 shows the estimated hazard ratios of the competing risk model, obtained by estimating a Cox PH model. The coefficients can be read as the ratio of the hazards of leaving unemployment implied by a one-unit change in the corresponding covariate. The proportionate change is obtained by subtracting one from the estimated hazard ratios provided in the Table.[43] One can see that, indeed, the measure of occupation employment risk seems to affect the hazard of leaving unemployment. In particular, a one-unit increase in the OER measure reduces the hazard of leaving unemployment to a job in the same occupation by more than 25%. In terms of standard deviations, an increase of one standard deviation in OER reduces the hazard of finding a job by 5.2% in each week of unemployment.[44] Therefore, all else equal, workers in occupations with a less diversified portfolio of employment opportunities (higher OER) face indeed longer unemployment spells than workers in occupations with more employment options (lower OER). With respect to leaving unemployment for a job in a different occupation, however, OER seems to have no effect.

Turning to other covariates, I find that being white increases the hazard of leaving unemployment for a job in the same occupation by 44.6%, but has no effect on leaving unemployment for a job in a different occupation. In comparison with high school dropouts, workers with a college degree have a 56.6% lower hazard rate of getting a job in the same occupation. An extra year of experience and tenure increases the hazard of leaving unemployment for a job in the same occupation by 14.7% and 23.1%, respectively. An

[43] Notice that the benchmark coefficient is one rather than zero since the hazard rate is the exponentiated coefficient.

[44] The mean and standard deviation values of OER are 0.06 and 0.20, respectively.

additional year of experience increases the hazard of getting a job in a different occupation by 6.1%, while an additional year of tenure reduces it by 17.7%. Having received unemployment insurance increases by 22.8% the hazard of leaving unemployment for a job in the same occupation, while it decreases by 27.3% the hazard of getting a job in a different occupation. A one percentage point increase in the local unemployment rate seems to have no effect on finding a job in the same occupation but reduces by 2.7% the hazard of finding a job in a different occupation.

4. OER Measure and Wage Change

In order to assess whether OER has any effect on earnings losses when controlling for other covariates, I examine its impact on the change in log wage between pre- and post-unemployment jobs. In particular, I estimate an Ordinary Least Squares regression, where unemployment spells are the unit of observation. Since the sample includes multiple spells per individual, I use clustered standard errors to account for the additional correlation. I estimate the following equation:

$$\Delta lnw = \beta_0 + \beta_1 OER + \beta_2 X + \beta_3 Z + \beta_4 slength + \varepsilon, \quad (6)$$

where X and Z are the same matrices of covariates used to estimate the effects of OER on the hazard rate of leaving unemployment, except for the unemployment rate and insurance compensation variables. All these covariates refer to pre- unemployment values. Total weeks of unemployment are represented by $slength$, which I expect to have a negative estimated coefficient, given that workers tend to lower their reservation wage as the length of their unemployment increases. In this context, when explicitly accounting for *slength* in the regression, its coefficient measures the effect of OER on wage changes through increases in unemployment duration and lower reservation wages while the OER coefficient measures its direct effect on wage gain or loss upon reemployment. In order to assess the total effect of OER on wage, I also run the regressions without spell length.

I examined the effect of OER on earnings losses for three different samples: occupation stayers, occupational switchers, and the full sample. I expect it to increase wage losses, especially for occupational switchers. The results are shown in Table 5. In fact, we can see that an increase in the OER measure increases the wage loss for all three samples. However, this effect is statistically significant only for occupational switchers (with and without spell length). In particular, a one-unit increase in the OER measure increases the hourly wage loss by 4.88% for all workers and by 11.5% for occupational switchers. For a one standard deviation increase in OER, the corresponding numbers are 1% and 2.3%, respectively. In addition, longer unemployment spells translate into higher wage losses, with each extra week of unemployment increasing the hourly wage loss by 0.1% for the full sample and by 0.2% for occupational stayers.[45] Similarly, an extra year of tenure increases wage loss by 2.1% for the full sample and by 6.2% for occupational switchers.

These results, combined with those for unemployment duration, suggest that workers in high-risk occupations, as defined by the OER measure, have an incentive to remain in the

[45] Thus high OER occupations face a 4.88% wage loss plus 0.1% for every extra week of unemployment, while workers in high OER occupations that switched occupations had an 11.5% wage loss of plus 0.2% for every extra week of unemployment.

same occupation in order to avoid incurring higher wage losses, even if this means facing longer unemployment spells.

5. Conclusions

This paper shows an aspect of human capital risk that seems to play an important role in explaining observable differences in unemployment duration and wage losses across occupations. I argue that this risk arises from large differences in the distribution of occupational employment across industries and from the fact that industries have different employment volatilities. These two facts imply that some occupations have a more diversified portfolio of employment opportunities, suggesting that individuals in these occupations potentially face lower unemployment risk than those in occupations with less diversification.

Using data from the decennial Census and the Quarterly Census of Employment and Wages, I estimate a measure of occupational employment risk (OER). I find a large variation in this risk across occupations. I then relate the OER measure to occupational unemployment durations and wage losses upon reemployment, using data from the NLSY79. Applying a competing risk duration model, I find that workers in high-risk occupations, as defined by the OER measure, have lower hazard ratios of leaving unemployment for a job in the same occupation and have higher wage losses than workers in low-OER occupations, especially if they switch occupations.

A next step in this research would be to investigate whether workers receive compensating wage differentials for this type of risk and how this risk relates to employment duration as well as to the incidence of unemployment. Preliminary exploration of this issue indicates that workers in high-OER occupations receive compensating differentials and have longer employment spells than workers in low-OER occupations. In particular, it would be interesting to estimate a multiple-state transition model with three possible labor market states—employment, unemployment, and out-of-the labor force—and examine the effects of the OER measure on the probabilities of exiting and entering these states. As in Martinez-Granado (2002), we could allow for unobservable individual heterogeneity, duration dependence, lagged duration dependence and state dependence. Another possibility would be to write a Mortensen-Pissarides model with the OER measure, which would sugesst that high-OER jobs should be more durable and have more flexible wages than low-OER jobs.

The type of risk documented and analyzed in this paper may affect the occupational and career choices of individuals, the search strategy of unemployed workers, and individual decisions about consumption and precautionary savings. With respect to career choice, we could ask if individuals take into account the risk associated with specific occupations when they make career choice decisions. With respect to the search strategy of unemployed individuals, it is worth noting that OER is closely related to the tradeoff between accepting a job today or waiting for a better offer tomorrow. As shown in this paper, the risk associated with specific occupations affects, on one hand, the wage that individuals receive upon reemployment and, on the other hand, the time they have to wait to receive an offer. It follows, then, that occupational employment risk may imply different outcomes in the optimal search of unemployed individuals.

Finally, it would be interesting to study whether OER affects precautionary savings and, if so, its implications for wealth holdings and consumption behavior. In the context of a life cycle model, the type of risk implied by occupational employment diversification can affect the employment transition matrix, which would affect optimal asset holdings. The relevant question would be to quantify this effect either with a realistic life cycle model or with some other empirical strategy.

Appendix

A.1 Weekly Labor Status

The NLSY79 Work History Data provide week-by-week records of the respondents labor force status from January 1, 1978, through the current survey date. At each year's survey, information is collected on jobs held and periods of not working since the date of the last interview.[46] Since the NLSY questions are constructed to collect a complete history for each respondent, regardless of period of noninterview, it is possible to construct for each respondent a continuous, week-by-week labor force status record.[47] In particular, the respondents' labor force history is constructed by filling in the weeks between the reported beginning and end dates for different activities (or "inactivities") with the appropriate labor status code.

One of the reported issues with the weekly labor status series is the presence of "split gaps" during unemployment, when individuals are unemployed for part of the gap and out of the labor force for the other part of it.[48] Since "split gaps" are coded such that the unemployment spell falls between two out-of-labor force spells, they are not considered to be completed unemployment spells and are therefore not included in the sample.

[46]A job held any day of a week is counted as a job for the whole week.

[47]For example, a respondent last interviewed in 1987, and not interviewed again until 1990, will have a complete labor force history, as information for the intervening period will be recovered in the 1990 interview. The NLSY "Work Experience" section reports that although there may be potential inconsistencies generated by this method, it does not compromise the quality and/or completeness of the work history record. For details, see Appendix 18 of the NLSY Documentation Files.

[48]Although the start and stop dates for the whole gap will be those actually reported by the respondent, the assignment of the unemployed and out-of-labor-force states will not represent actual dates reported by the respondent. Instead, they represent only the number of weeks that a respondent reported having held each status, with the unemployed status being arbitrarily assigned to the middle portion of the gap. For further details on "split gaps," see Appendix 18 in the NLSY documentation.

The NLSY weekly labor status variable, *wk*, can assume the following values:

$$wk = \begin{cases} 0, & \text{cannot account for week due to invalid start and end dates;} \\ 2, & \text{cannot determine whether unemployed or out-of-the labor force;} \\ 3, & \text{employed but cannot account for all of the time with employer;} \\ 4, & \text{unemployed;} \\ 5, & \text{out of the labor force;} \\ 7, & \text{active military service;} \\ >7, & \text{employed.} \end{cases}$$

For about 1% of the weeks in the male, nonmilitary sample *wk* is equal to 0. When employed, the assigned code is the actual survey number multiplied by 100 plus the job number for that employer in that year. Based on this classification, I generated a weekly employment status that assumes the following values:[49]

$$empstat = \begin{cases} employed & \text{if } wk = 3 \text{ or } >7 \\ unemployed & \text{if } wk = 4 \text{ or } (wk_t=2)\&(2 \leq wk_{t-1} \leq 4) \text{ or } (wk_t=2)\&(wk_{t-1}>7) \\ other & \text{if empstat} \neq 1 \text{ or } 2 \end{cases}$$

A.2 Industry and Occupational Codes

The Census defines an industry as a group of establishments that produce similar products or provide similar services. Although many industries are closely related, each has a unique combination of inputs and outputs, production techniques, occupations, and business

[49] It is worth noting that I do not include individuals who ever worked in the military.

characteristics. Occupations are classified based on work performed, skills, education, training, and credentials. The classification system covers all occupations in which work is performed for pay or profit and is intended to classify workers at the most detailed level possible.

The universe used by the Census for occupation and industry variables comprises individuals age sixteen or older who worked within the previous five years and are not considered new workers.[50] Occupation and industry codes report the person's primary occupation and industry, which are considered to be the ones in which the person earns the most money; however, for respondents unsure about their income, their primary occupation and industry were considered those at which they spent the most time. If a person listed more than one occupation and/or industry, the samples use the first one listed. The occupational codes were assigned based on the following two questions: (1) What kind of work was this person doing? and (2) What were this person's most important activities or duties? The industry codes were assigned based on the following three questions: (1) For whom did this person work (name of company, business, organization, or other employer)? (2) What kind of business or industry was this? and (3) Is it mainly manufacturing, wholesale trade, retail trade, or other?

Matching Industry Codes

In order to estimate the OER measure, I calculate the concentration of occupational employment across industries and the volatility and comovement of disaggregated industry

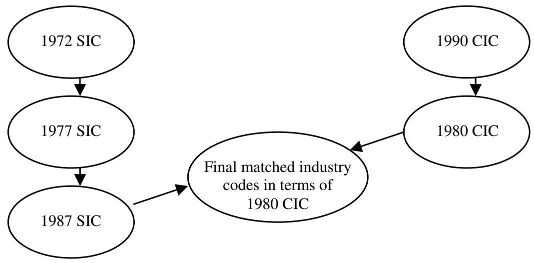
[50] "New workers" are defined as persons seeking employment for the first time who have not yet secured their first job.

employment. Given the fact that there is no single data set with occupational employment by industry during the period of analysis (1979-2000), I combine data from two different sources to compute both components of the OER measure.

I use data from the 1990 Census to calculate the concentration component of the OER measure, which is obtained by calculating the shares of occupational employment in each industry. The volatility component was estimated using data from the Quarterly Census of Employment and Wages (QCEW), 1978-2000. However, these two data sources use different industry classification systems. The Census uses the Census Industrial Classification (which I will call CIC), while the QCEW uses the Standard Industrial Classification (SIC) System. In order to estimate OER from these two data sets, I need to match the industry codes across the industry classification systems. In addition, both classification systems experience changes over time. Therefore, it is necessary to match industry codes across classification systems and over time in order to have consistent industry codes over the period of analysis. An extensive discussion of all criteria applied in this matching is given in Tristao (2005). I choose the 1980 Census industry and occupational codes as the base codes for this study. I discuss the occupational codes' matching in the next subsection.

Over time changes within classification systems can be mainly classified into three categories: (1) change in the code value assigned for a given industry; (2) merges and splits in existing industry codes, resulting in the creation of a new code or disappearance of an existing one; and (3) new industry codes due to a new industry in the economy. The changes between the 1980 and 1990 CIC systems were minimal and the criteria I use to deal with them can be summarized by using the corresponding 1980 code for changes of type (1),

Figure A: Industry Codes' Matching



combining industry codes into a single code for changes of type (2), and adding new codes to the closest miscellaneous category with a correspondence in 1980 codes for type (3).

The QCEW data use the 1972 SIC codes for the years 1975-1987 and the 1987 SIC codes for the period 1988-2000. The match within the SIC system was made through the correspondences offered by the 1987 Standard Industrial Classification manual, which provides a 4-digit code crosswalk between the 1972 and 1977 SICs and between the 1977 and 1987 SICs. Based on this crosswalk, I merge 3-digit industry codes if one or more of their 4-digit industries are reported to be combined. I choose the 1987 SIC codes as the base code for this particular match.

In order to merge the Census industry codes and the Standard Industrial Classification codes, I use a Census crosswalk between the 1990 Census industry codes and the 1987 SIC codes. The match between these two systems required further 3-digit industry code merges to maintain group comparability across classification systems and time.[51] After the matches, I

[51] See Census Technical Paper 65, The Relationship Between the 1990 Census and Census 2000 Industry and Occupation Classification Systems.

obtain 158 industry codes, a 33% reduction from the number of 3-digit industries in the 1980 and 1990 CIC codes. Figure A.1 illustrates the match.

Matching Occupation Codes

The OER measure is calculated for every CPS detailed occupational code based on the 1980 Census occupational codes. However, the data for calculating the shares of occupational employment across industries come from the 1990 Census PUMS, which uses the 1990 Census occupational codes. Therefore, in order to have consistent occupational codes, I match the codes between both classification systems. The changes between them were minimal and can be classified into two types: (1) a change in the code value assigned for a given occupation, and (2) merges and splits in existing industry codes, resulting in the creation of a new code or the disappearance of an existing one. The procedure I apply in matching the codes is to use the corresponding 1980 code for changes of type (1), and to combine occupational codes into a single code for changes of type (2).

The data set I use to assess the relevance of the OER measure for unemployment duration and wage changes is the National Longitudinal Survey of Youth 1979 (NLSY79). The NLSY79 uses the 1970 Census occupational codes in reporting the occupations for up to five jobs each individual held during any survey round.[52] Since the OER measure is calculated for 1980 Census occupational codes, I match the 1970 Census occupational code to the 1980 Census codes. It is worth noting that there are significant changes between these two classification systems. The Bureau of Census Technical Paper 59 (The Relationship

[52] For the main job or CPS job only, it also provides the 1980 Census occupational codes.

Between the 1970 and 1980 Industry and Occupation Classification Systems) provides, for each occupation, a quantification of the employment relationship between these two systems, which I use in generating the correspondences between them. For each 1970 occupational code, I assign the 1980 occupational code that received the largest share of the 1970 occupational code's employment. For 76% of all occupations in the 1970 code, more than 75% of their employment correspond to a single occupation code in 1980.[53]

A.3 Construction of Age-Adjusted Ability Measure

The measures of ability used in this paper are calculated from the Armed Services Vocational Aptitude Battery (ASVAB), a set of ten tests that measure knowledge and skill in the following areas: (1) general science, (2) arithmetic reasoning, (3) word knowledge, (4) paragraph comprehension, (5) numerical operations, (6) coding speed, (7) auto and shop information, (8) mathematical knowledge, (9) mechanical comprehension, and (10) electronics information.

Since the NLSY79 respondents had different ages and educational levels when they took the tests, and the scores on these "ability" tests may increase with age and education, it was necessary to adjust the ASVAB test scores for both factors. I follow the two-step methodology presented by Cawley et al. (1995) and Kermit et al. (2005), which uses principal components analysis in order to measure age-adjusted ASVAB scores.

The ASVAB scores are adjusted for age by regressing each test score on age dummy

[53] For around 40% of all occupations in the 1970 code over 99% of their employment corresponded to a single occupation code in 1980, while for 86% over 50% of employment corresponded to a single occupation code in 1980. Only 3.4% of all occupations in the 1970 code had the highest percentage of their employment assigned to a 1980 code as less than 50%.

Table A.1 : **ASVAB Principal Components**

Component	Eigenvalue	Difference	Proportion	Cumulative
1	6.74144	5.81295	0.6741	0.6741
2	0.9285	0.37823	0.0928	0.767
3	0.55027	0.10989	0.055	0.822
4	0.44038	0.13468	0.044	0.8661
5	0.30571	0.03699	0.0306	0.8966
6	0.26871	0.04837	0.0269	0.9235
7	0.22034	0.0115	0.022	0.9455
8	0.20884	0.02749	0.0209	0.9664
9	0.18134	0.02687	0.0181	0.9846
10	0.15448	.	0.0154	1
Eigenvectors, 1st and 2nd PC	**1st PC**	**2nd PC**		
General science residuals	0.34016	-0.17568		
Arithmetic reasoning residuals	0.33150	0.13789		
Word knowledge residuals	0.34340	-0.07447		
Paragraph comprehension residuals	0.32602	0.02441		
Numerical operations residuals	0.28267	0.52215		
Coding speed residuals	0.27085	0.49544		
Auto and shop knowledge residuals	0.29872	-0.43598		
Mathematical knowledge residuals	0.31038	0.23927		
Mechanical comprehension residuals	0.32052	-0.28386		
Electrical information residuals	0.32958	-0.31302		

variables and an indicator variable of whether the respondent had completed high school when the tests were administered (Kermit et al. (1995)). Principal components analysis is performed on the ordinary least squares residuals from these regressions. See Heckman (1995) on using the first two principal components and Kermit et al. (2005) for an application of this procedure. The estimates are presented in Table A.1.

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Table 1: Average Unemployment Duration and Wage Change by Occupation

Current Population Survey Detailed Occupation Title	Duration	Std. Err.	Change in Log Wage	Std. Err.
Public Administration	8.87	(3.03)	0.26	(0.07)
Executives, Administrators, and Managers, exc. Pub. Adm.	10.04	(0.78)	-0.06	(0.04)
Management-Related Occupations	12.79	(1.93)	-0.06	(0.06)
Engineers	9.16	(1.67)	-0.16	(0.11)
Mathematical and Computer Scientists	14.87	(4.54)	-0.05	(0.13)
Natural Scientists	4.51	(1.87)	-	-
Health Diagnosing Occupations	6.06	(3.54)	-	-
Health Assessment and Treatment Occupations	8.27	(2.94)	-0.06	(0.05)
Teachers, College and University	11.06	(5.97)	-0.01	(0.27)
Teachers, Except College and University	5.73	(1.15)	-0.07	(0.07)
Lawyers and Judges	14.17	(3.04)	-0.01	(0.11)
Other Professional Specialty Occupations	9.15	(0.96)	0.11	(0.07)
Health Technologists and Technicians	6.40	(2.02)	0.17	(0.12)
Engineering and Science Technicians	10.77	(1.47)	-0.05	(0.07)
Technicians, Except Health, Engineering, and Science	6.94	(1.50)	0.14	(0.06)
Sales Representatives, Finance, and Business Service	11.35	(2.12)	-0.02	(0.05)
Sales Representatives, Commodities, Except Retail	10.83	(1.16)	-0.17	(0.05)
Sales Workers, Retail and Personal Services	12.22	(1.90)	0.03	(0.07)
Supervisors - Administrative Support	9.20	(2.96)	-	-
Computer Equipment Operators	22.41	(6.36)	0.21	(0.15)
Secretaries, Stenographers, and Typists	7.37	(1.70)	-0.03	(0.14)
Financial Records, Processing Occupations	6.44	(1.47)	0.01	(0.04)
Mail and Message Distributing	10.42	(1.92)	0.04	(0.02)
Other Administrative Support Occupations, Including Clerical	9.10	(0.79)	0.01	(0.04)
Private Household Service Occupations	5.52	(0.64)	-	-
Protective Service Occupations	11.95	(1.81)	-0.07	(0.05)
Food Service Occupations	10.57	(0.80)	0.01	(0.03)
Health Service Occupations	11.23	(2.08)	0.00	(0.03)
Cleaning and Building Service Occupations	13.31	(1.42)	0.05	(0.04)
Personal Service Occupations	10.55	(3.34)	-0.06	(0.07)
Mechanics and Repairers	10.31	(0.78)	0.00	(0.03)
Construction Trades	9.61	(0.58)	0.01	(0.02)
Other Precision Production Occupations	11.01	(0.89)	-0.01	(0.03)
Machine Operators and Tenders, Except Precision	9.41	(0.71)	-0.02	(0.02)
Fabricators, Assemblers, Inspectors, and Samplers	9.18	(0.70)	0.02	(0.02)
Motor Vehicle Operators	10.02	(0.84)	0.01	(0.04)
Other Transportation Occupations and Material Moving	11.19	(1.18)	-0.03	(0.02)
Construction Laborers	9.72	(0.57)	0.01	(0.03)
Freight, Stock and Material Handlers	11.01	(0.97)	-0.02	(0.04)
Other Handlers, Equipment Cleaners, and Laborers	11.62	(0.87)	0.02	(0.04)
Farm Operators and Managers	9.11	(2.94)	0.40	(0.28)
Farm Workers and Related Occupations	12.22	(0.79)	0.03	(0.04)
Forestry and Fishing Occupations	6.49	(1.24)	0.15	(0.10)
Overall	10.05	(1.86)	0.02	(0.07)
Number of observations	5,425		3,619	
Number of clusters	2,251		1,778	
F-Test*	1.85		1.92	
Prob $>$ F	0.0008		0.0003	

*F-test for equality of duration and wage loss across occupations. Across industries, we cannot reject the null hypothesis of equality. There are few occupations with no observations for wage change.
Source: NLSY79, 1979-2000.

Table 2: Measure of Occupational Employment Concentration

Current Population Survey Detailed Occupation Title	# 3-digit Industries	Herfindahl Index
Public Administration	22	0.162
Other Executives, Administrators, and Managers	158	0.035
Management-Related Occupations	156	0.046
Engineers	147	0.103
Mathematical and Computer Scientists	138	0.065
Natural Scientists	114	0.076
Health Diagnosing Occupations	51	0.461
Health Assessment and Treatment Occupations	103	0.421
Teachers, College and University	27	0.951
Teachers, Except College and University	114	0.720
Lawyers and Judges	99	0.580
Other Professional Specialty Occupations	154	0.054
Health Technologists and Technicians	87	0.346
Engineering and Science Technicians	149	0.073
Technicians, Exc. Health, Engineering, and Science	146	0.045
Supervisors and Proprietors, Sales Occupations	148	0.065
Sales Representatives, Finance, and Business Service	93	0.348
Sales Representatives, Commodities, Exc. Retail	100	0.089
Sales Workers, Retail and Personal Services	140	0.083
Sales-Related Occupations	52	0.125
Supervisors - Administrative Support	152	0.042
Computer Equipment Operators	152	0.034
Secretaries, Stenographers, and Typists	157	0.038
Financial Records, Processing Occupations	157	0.027
Mail and Message Distributing	130	0.454
Other Adm. Support Occupations, Incl. Clerical	158	0.035
Private Household Service Occupations	1	1.000
Protective Service Occupations	147	0.343
Food Service Occupations	133	0.505
Health Service Occupations	85	0.257
Cleaning and Building Service Occupations	156	0.079
Personal Service Occupations	108	0.190
Mechanics and Repairers	157	0.054
Construction Trades	150	0.551
Other Precision Production Occupations	155	0.105
Machine Operators and Tenders, Except Precision	158	0.067
Fabricators, Assemblers, Inspectors, and Samplers	155	0.115
Motor Vehicle Operators	156	0.106
Other Transportation Occupations and Material Moving	145	0.090
Construction Laborers	111	0.833
Freight, Stock and Material Handlers	149	0.157
Other Handlers, Equipment Cleaners, and Laborers	157	0.028
Farm Operators and Managers	3	0.474
Farm Workers and Related Occupations	119	0.205
Forestry and Fishing Occupations	51	0.309

Sources: 1990 Census Public Use Microdata Series (PUMS).

Table 3: Sample Statistics

Variables	All sample	Stayers	Switchers
Age	28.12	27.56	26.63
	(0.11)	(0.24)	(0.17)
White	79.94%	84.43%	76.53%
Married	45.26%	40.86%	52.00%
Years Schooling	12.19	11.86	12.03
	(0.06)	(0.10)	(0.11)
HS	70.30%	72.62%	68.80%
College	8.63%	4.18%	7.50%
Experience	5.02	4.68	3.81
	(0.10)	(0.21)	(0.14)
Tenure	1.34	1.62	0.86
	(0.07)	(0.18)	(0.04)
Received UI	41.32%	55.49%	34.39%
Displaced	19.93%	14.24%	24.40%
Number of spells	5,425	1,479	1,158
N. of clusters	2,251	756	746

Notes: (1) Standard deviations are in parentheses; (2) 2,741 unemployment spells (out of 5,344) did not report occupational code either for the previous or the new job or both. Source: NLSY79, 1979-2000.

Table 4: Unemployment Duration: Cox PH Estimated Hazards

	Same Occupation		Different Occupation	
	coef.	std	coef.	std
OER	0.743	(0.124)†*	0.981	(0.196)
White	1.446	(0.132)**	0.992	(0.085)
Age	0.769	(0.143)	1.149	(0.257)
Age^2	1.004	(0.003)	0.996	(0.004)
Ability Factor 1	1.031	(0.021)	1.009	(0.018)
Ability Factor 1^2	0.997	(0.006)	0.997	(0.004)
Ability Factor 2	1.049	(0.044)	0.932	(0.042)
Ability Factor 2^2	1.017	(0.031)	0.974	(0.032)
High school	1.034	(0.099)	1.012	(0.090)
College	0.434	(0.120)**	0.918	(0.159)
Married	0.920	(0.072)	1.020	(0.082)
Experience	1.147	(0.070)*	1.061	(0.074)
Experience^2	0.992	(0.004)†	1.000	(0.006)
Tenure	1.231	(0.063)**	0.823	(0.061)**
Tenure^2	0.989	(0.005)*	1.014	(0.010)
Unemployment Insurance	1.228	(0.095)**	0.727	(0.059)**
Unemp. Rate	1.000	(0.016)	0.973	(0.013)*
N. of spells	4,929		4,929	
N. of clusters	2,065		2,065	
Wald chi2(17)	121.42		48.08	

**, *, †: significant at 1%, 5%, and 10%, respectively; †*: significant at 8%. Notes: (1) Standard deviations are in parentheses; (2) Ability factors 1 and 2 are principal components the first two of the age-adjusted ASVAB scores. Source: NLSY79, 1979-2000.

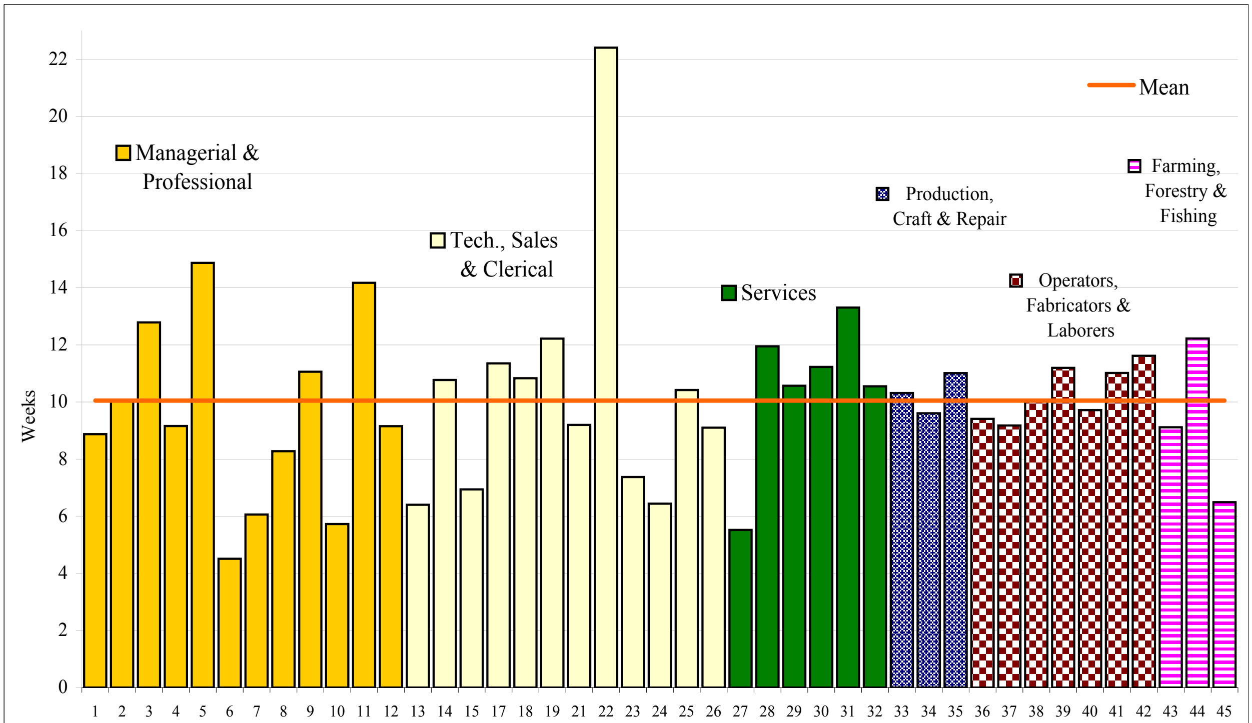
Table 5: Wage Change: OLS Estimates

	All sample		Stayers		Switchers	
OER	-0.04882	-0.05233	-0.00505	-0.01145	-0.11451	-0.11500
	(0.03513)	(0.03491)	(0.05019)	(0.04958)	(0.05414)*	(0.05418)*
White	-0.01447	-0.01193	-0.01319	-0.01060	-0.02328	-0.02284
	(0.01511)	(0.01499)	(0.01561)	(0.01548)	(0.03587)	(0.03582)
Age	-0.01539	-0.01191	-0.01328	-0.01076	-0.02471	-0.01864
	(0.02843)	(0.02866)	(0.02760)	(0.02788)	(0.06519)	(0.06515)
Age^2	0.00028	0.00021	0.00023	0.00017	0.00043	0.00032
	(0.00049)	(0.00050)	(0.00048)	(0.00049)	(0.00111)	(0.00111)
Ability Factor 1	0.00326	0.00366	0.00375	0.00430	0.00285	0.00324
	(0.00372)	(0.00374)	(0.00375)	(0.00379)	(0.00867)	(0.00864)
Ability Factor 1^2	0.00045	0.00040	-0.00026	-0.00019	0.00246	0.00225
	(0.00111)	(0.00112)	(0.00121)	(0.00122)	(0.00241)	(0.00239)
Ability Factor 2	0.01511	0.01460	0.01772	0.01772	0.01340	0.01232
	(0.00743)*	(0.00743)*	(0.00785)*	(0.00785)*	(0.01536)	(0.01528)
Ability Factor 2^2	0.00505	0.00498	0.00747	0.00796	0.00343	0.00280
	(0.00464)	(0.00466)	(0.00489)	(0.00497)	(0.00980)	(0.00978)
High School	0.00703	0.01231	-0.00436	0.00059	0.03728	0.04314
	(0.01822)	(0.01836)	(0.01637)	(0.01666)	(0.04525)	(0.04479)
College	-0.03445	-0.02905	-0.00214	0.00294	-0.05741	-0.04974
	(0.03952)	(0.03974)	(0.04666)	(0.04681)	(0.06894)	(0.06871)
Married	0.01805	0.01603	-0.00446	-0.00666	0.06441	0.06326
	(0.01513)	(0.01521)	(0.01557)	(0.01574)	(0.03295)	(0.03306)†
Experience	0.00326	0.00350	-0.00211	-0.00201	0.02008	0.02044
	(0.01003)	(0.01004)	(0.00881)	(0.00883)	(0.02277)	(0.02271)
Experience^2	-0.00001	-0.00001	0.00000	0.00000	-0.00002	-0.00002
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00003)	(0.00003)
Tenure	-0.02110	-0.02126	-0.01123	-0.01140	-0.06172	-0.06297
	(0.00829)*	(0.00836)*	(0.00752)	(0.00759)	(0.02680)*	(0.02693)*
Tenure^2	0.00004	0.00004	0.00002	0.00002	0.00011	0.00011
	(0.00002)*	(0.00002)*	(0.00001)	(0.00001)	(0.00006)	(0.00006)†
Spell Length	-0.00137		-0.00175		-0.00094	
	(0.00047)**		(0.00060)**		(0.00076)	
Constant	0.23556	0.17132	0.24317	0.19142	0.29421	0.19481
	(0.39435)	(0.39557)	(0.37861)	(0.38099)	(0.91489)	(0.91009)
Number of spells	3,462	3,462	2,212	2,212	1,250	1,250
Number of clusters	1,691	1,691	1,246	1,246	884	884
F-Test	1.78	1.35	1.30	0.97	1.71	1.61
Prob $>$ F	0.0290	0.1619	0.1864	0.4836	0.0390	0.0660
R-squared	0.0112	0.0127	0.0248	0.0071	0.0070	0.0227

**, *, †: significant at 1%, 5%, and 10%, respectively.

Notes: (1) Standard deviations are in parentheses; (2) Ability factors 1 and 2 are the first two principal components of the age-adjusted ASVAB scores. Source: NLSY79, 1979-2000.

Figure 1: Average Unemployment Duration by Occupation

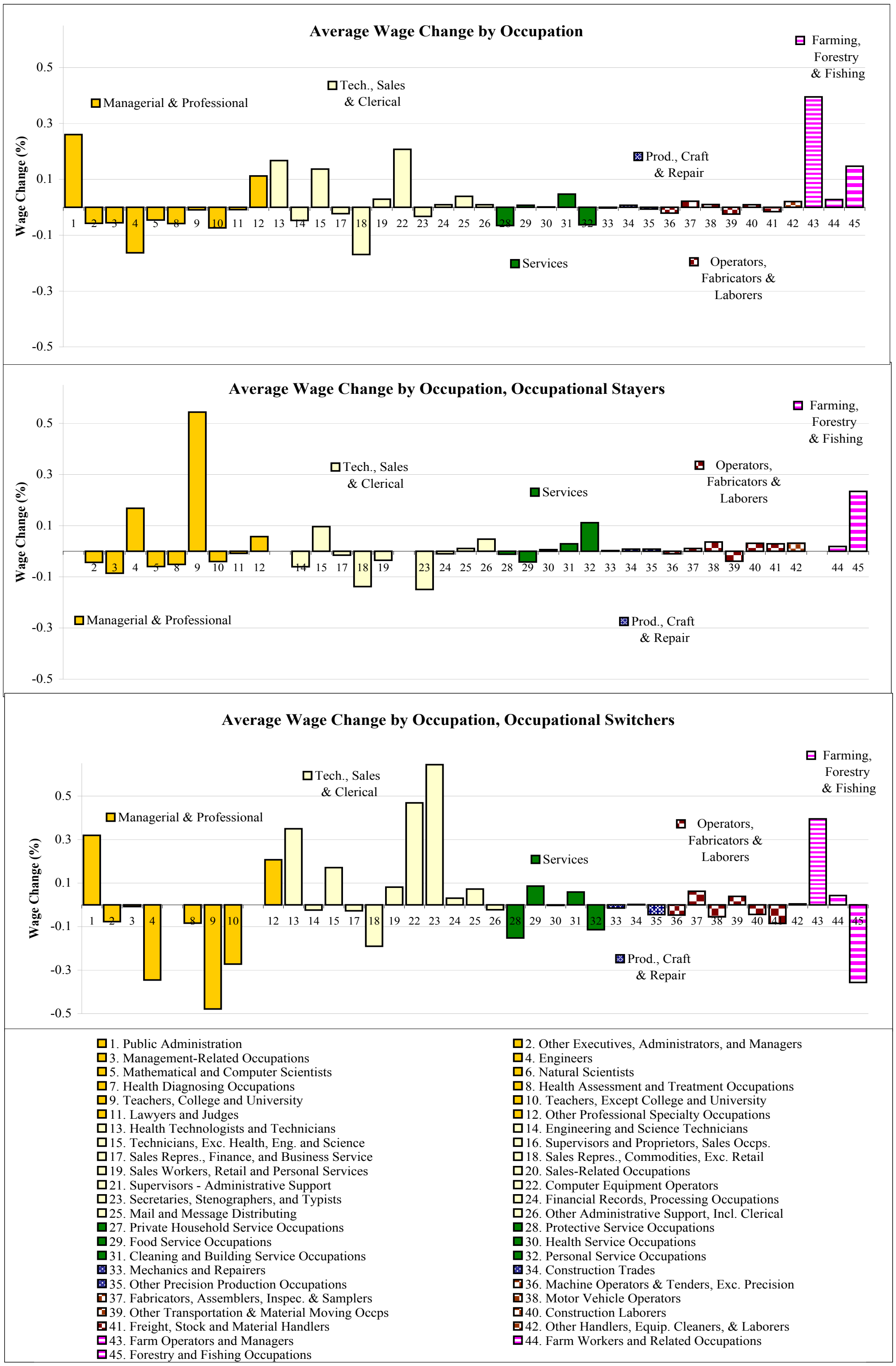


1. Public Administration
2. Other Executives, Administrators, and Managers
3. Management-Related Occupations
4. Engineers
5. Mathematical and Computer Scientists
6. Natural Scientists
7. Health Diagnosing Occupations
8. Health Assessment and Treatment Occupations
9. Teachers, College and University
10. Teachers, Except College and University
11. Lawyers and Judges
12. Other Professional Specialty Occupations
13. Health Technologists and Technicians
14. Engineering and Science Technicians
15. Technicians, Exc. Health, Eng. and Science
16. Supervisors and Proprietors, Sales Occps.
17. Sales Repres., Finance, and Business Service
18. Sales Repres., Commodities, Exc. Retail
19. Sales Workers, Retail and Personal Services
20. Sales-Related Occupations
21. Supervisors - Administrative Support
22. Computer Equipment Operators
23. Secretaries, Stenographers, and Typists
24. Financial Records, Processing Occupations
25. Mail and Message Distributing
26. Other Administrative Support, Incl. Clerical
27. Private Household Service Occupations
28. Protective Service Occupations
29. Food Service Occupations
30. Health Service Occupations
31. Cleaning and Building Service Occupations
32. Personal Service Occupations
33. Mechanics and Repairers
34. Construction Trades
35. Other Precision Production Occupations
36. Machine Operators & Tenders, Exc. Precision
37. Fabricators, Assemblers, Inspec. & Samplers
38. Motor Vehicle Operators
39. Other Transportation & Material Moving Occps
40. Construction Laborers
41. Freight, Stock and Material Handlers
42. Other Handlers, Equip. Cleaners, & Laborers
43. Farm Operators and Managers
44. Farm Workers and Related Occupations
45. Forestry and Fishing Occupations

Source: NLSY79, 1979-2000.

*Occupations omitted from the graph had no observations.

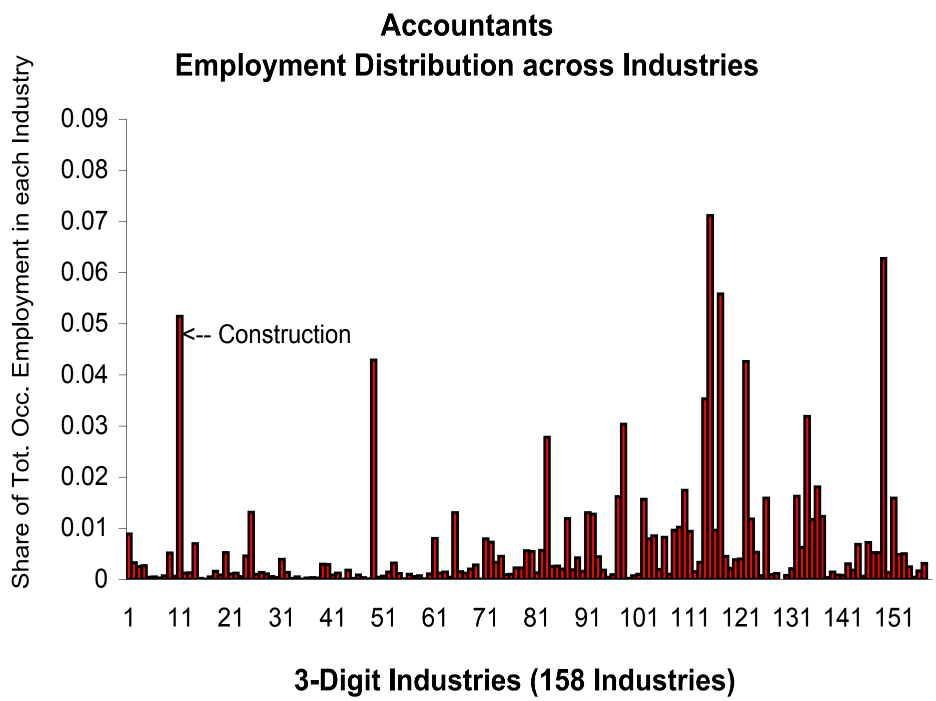
Figure 2: Average Wage Change by Occupation

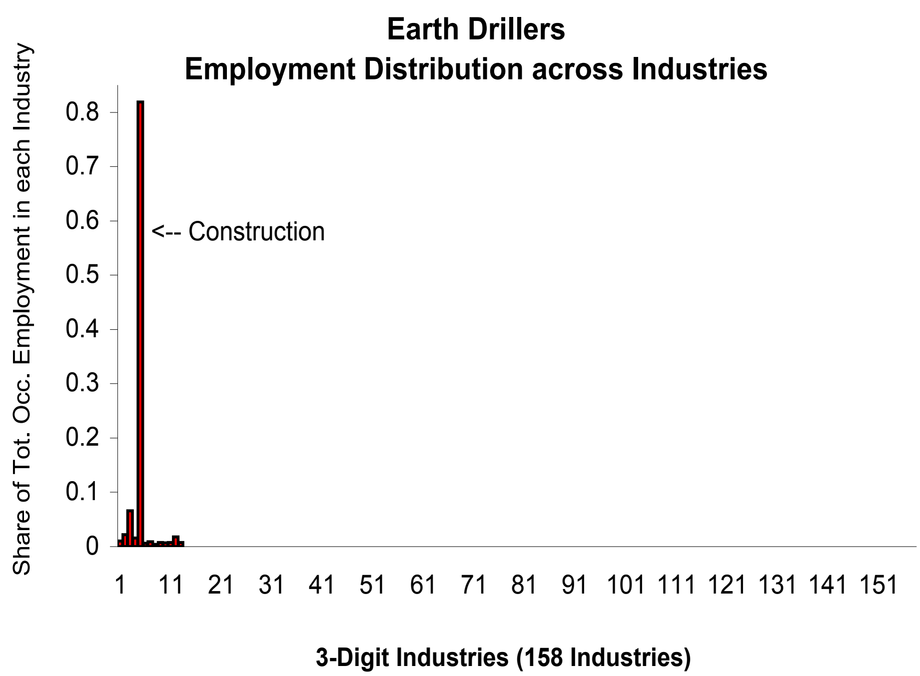


Source: NLSY79, 1979-2000.

*Occupations omitted from the graph had no observations.

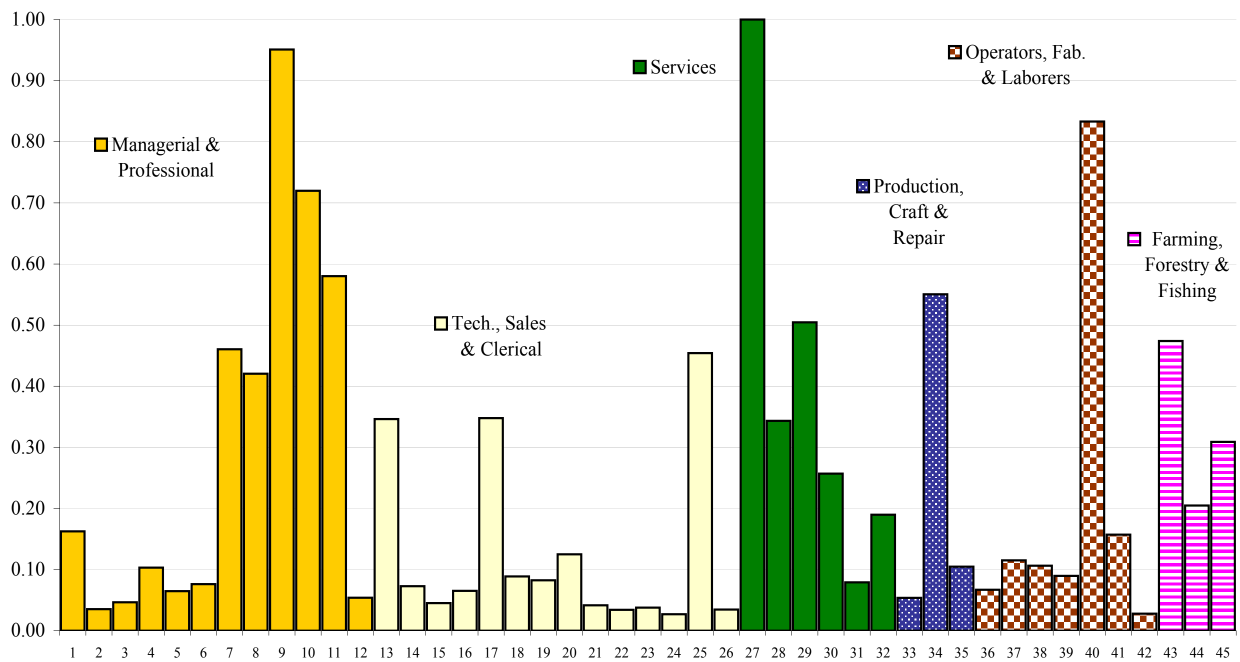
Figure 3: Accountants and Earth Drillers Employment Distribution across Industries





Source:1990 Census Public Use Microdata Series(PUMS).

Figure 4: Herfindahl Index of Employment Concentration by Occupation



1. Public Administration
2. Other Executives, Administrators, and Managers
3. Management-Related Occupations
4. Engineers
5. Mathematical and Computer Scientists
6. Natural Scientists
7. Health Diagnosing Occupations
8. Health Assessment and Treatment Occupations
9. Teachers, College and University
10. Teachers, Except College and University
11. Lawyers and Judges
12. Other Professional Specialty Occupations
13. Health Technologists and Technicians
14. Engineering and Science Technicians
15. Technicians, Exc. Health, Eng. and Science
16. Supervisors and Proprietors, Sales Occps.
17. Sales Repres., Finance, and Business Service
18. Sales Repres., Commodities, Exc. Retail
19. Sales Workers, Retail and Personal Services
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21. Supervisors - Administrative Support
22. Computer Equipment Operators
23. Secretaries, Stenographers, and Typists
24. Financial Records, Processing Occupations
25. Mail and Message Distributing
26. Other Administrative Support, Incl. Clerical
27. Private Household Service Occupations
28. Protective Service Occupations
29. Food Service Occupations
30. Health Service Occupations
31. Cleaning and Building Service Occupations
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33. Mechanics and Repairers
34. Construction Trades
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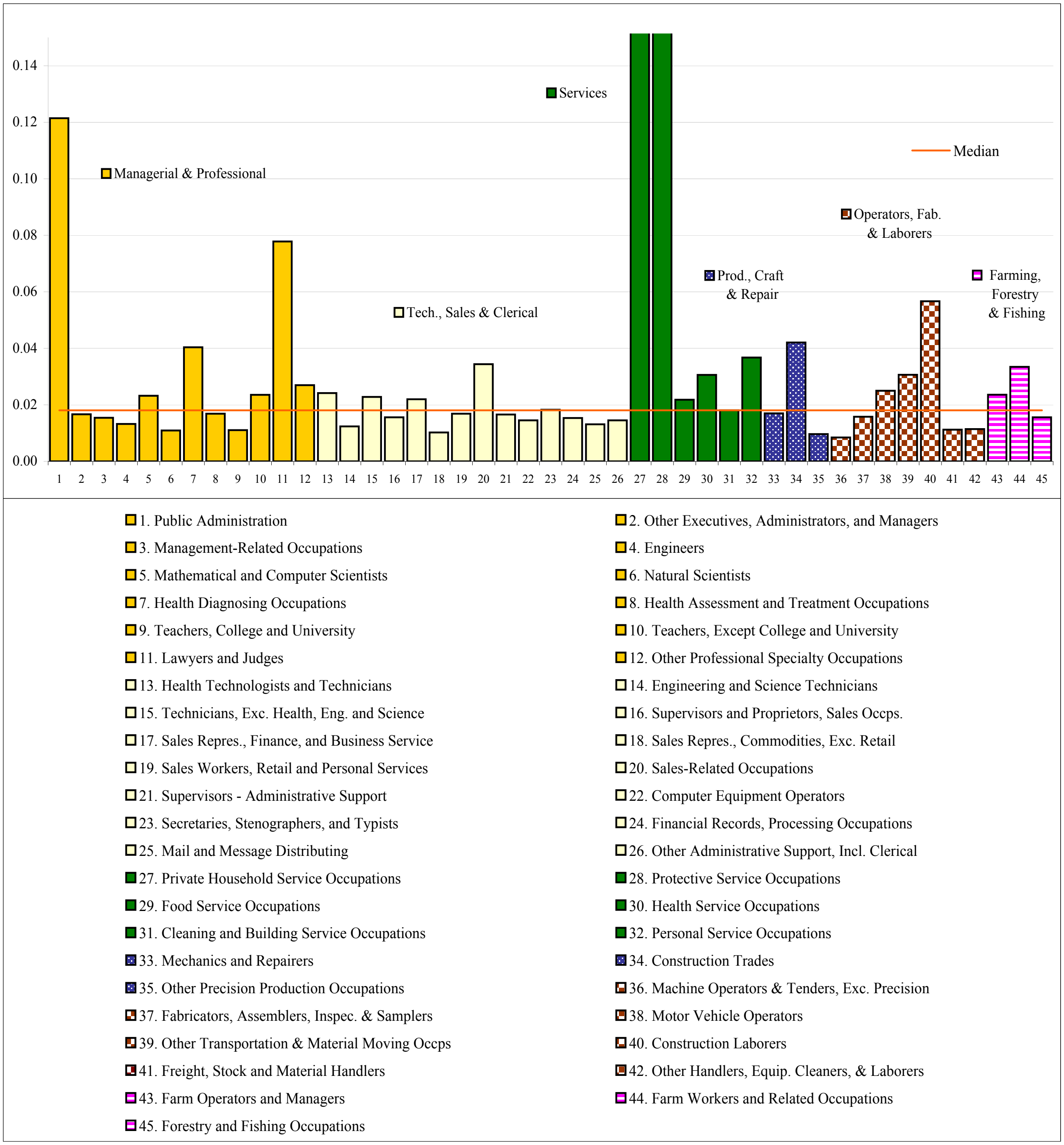
38. Motor Vehicle Operators
39. Other Transportation & Material Moving Occps
40. Construction Laborers
41. Freight, Stock and Material Handlers
42. Other Handlers, Equip. Cleaners, & Laborers
43. Farm Operators and Managers
44. Farm Workers and Related Occupations
45. Forestry and Fishing Occupations

Sources: 1990 Census Public Use Microdata Series and Quarterly Census of Employment and Wages, 1978-2000.

Figure 5: Occupational Employment Risk Measure



*OER for occupations 27 and 28 is 0.30 and 1.35, respectively. The graph is truncated at 0.15 for better visualization.

Sources: 1990 Census Public Use Microdata Series and Quarterly Census of Employment and Wages, 1978-2000.