How Hard Is It to Get Another Job?

Occupational Employment Risk and its Consequences for Unemployment Duration and Wages

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December 2005

Abstract

There are substantial differences in unemployment durations and reemployment outcomes for workers coming from different occupations. I argue that this variation can be explained in part by differences in occupational employment risk, which arise from two sources: (1) the diversification of occupational employment across industries; and (2) the volatility of industry employment fluctuations, including sectoral comovements. I define and construct a measure of occupational employment risk (OER) which I estimate using the Quarterly Census of Employment and Wages, years 1979-2000. Using the NLSY79 male sample, I construct a weekly panel of employment and demographic histories, which includes employer characteristics for up to five jobs each individual held during any year in the period 1979-2000. I then relate the OER measure to occupational unemployment durations and wage losses. Applying a competing risk duration model, I find that unemployed workers in high risk occupations, as defined by the OER measure, have 5% 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 risk OER occupations. Among occupational switchers, workers in high risk OER occupations have 11% higher wage losses than workers in OER occupations.

[1]I want to thank John Rust, Seth Sanders and John Shea for advising me in this work and providing continuous support. I also want to thank Jeffrey Smith, Judith Hellerstein, Bill Evans and Mark Duggan for helpful comments and suggestions. I am indebted to Jay Zagorsky and Steve McClaskie from the Center for Human Resource Research (CHRR) for providing expert advise on the use of NLSY data. Discussions with Alex Whalley and Juan Contreras helped me to improve this paper. All errrors are my own.
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1 Introduction

This paper documents substantial differences in unemployment durations and reemployment outcomes across workers coming from different occupations. It argues that this variation can be in part explained by differences in occupational employment diversification, arising from differences in the distribution of occupational employment across industries and from the variation in industry employment volatilities.

Table 1 shows average unemployment durations and wage changes upon reemployment across occupations. Figures 1 and 2 present the information graphically. They show a large variation in unemployment spell durations and wage losses across occupations, even among closely related occupational groups.[2] In particular, the wage loss variation is present regardless of whether workers switched occupations or not upon reemployment, or whether they were displaced or not (see figure 3).[3] For instance, comparing two low skill blue-collar occupations such as 'cleaning and building services' and 'handlers and laborers,' we find large differences in spell duration and wage losses. Similarly, comparing the two closely related white collar occupations 'engineering and science technicians' and 'other technicians', we find that the workers in the former occupation have much higher unemployment durations and wage losses than those in the later.

From table 1 and figures 1 to 3, it is evident that differences in unemployment duration and wage losses are present even within major occupation groups that combine occupations with similar skills, education, training, and work performed. 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.

Past studies of unemployment duration and wage determination have acknowledged the relevance of occupation either directly, by differentiating workers between blue and white collar or main occupational groups, or indirectly by controlling for occupation in their analysis. Few studies, however, have tried to investigate why occupations are important to employment and wages. Occupations are, in general, classified based on an exclusive set of specific skills and skill demands which uniquely define them.[4] Recent studies suggest that occupation captures

[2]The statistics are reported for 45 'detailed' occupational codes, which is an intermediate occupational classification (between two and three-digit occupational codes) given by the Current Population Survey (CPS). The data source for table 1 is the NLSY79, 1979-2000. Occupations with less than twenty observations are omitted from the analysis.

[3]Displaced workers are workers that report losing their jobs due to layoff or plant closing.

[4]Occupations are classified based upon work performed, skills, education, training, and credentials. Occupa-

an important component of human capital which is relevant to earnings determination.[5] In particular, they find that when occupation-specific human capital or a set of skills specific to occupations are taken into account, industry and firm-specific human capital lose their importance in explaining earnings.

Moreover, it has become common in the literature to consider that individuals with different skills or levels of accumulated human capital face different labor income and/or employment risk. Most studies measure human capital risk as differences in the incidence of unemployment or in the variance of labor income associated with different levels of skills.[6] In this paper, however, I show that there is another aspect of human capital risk that has not been studied before and that seems to have an important role in explaining observable differences in unemployment duration and wage losses across occupations.

In particular, the dimension of human capital risk that I analyze concerns 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, suggesting that the individuals employed in more diversified occupations potentially face lower unemployment risk than individuals employed in occupations with lower diversification. I call this phenomenon Occupational Employment Risk (OER).

Regarding the occupational employment distribution, occupations can differ in two important dimensions. First, occupations vary in the number of different industries that employ them. For instance, using 1990 Census data, the occupation 'assemblers' is common to 146 out of 158 three-digit industries, while the occupation 'shoe machine operator' is only employed by 10 of these industries. Second, occupations vary enormously with respect to the concentration of their employment across industries. In fact, 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 the Herfindahl Index of concentration or H-Index, as it is also known.[7] Table 2 presents the Herfindahl index for each occupation.

tion classification systems cover all occupations in which work is performed for pay or profit, and it is intended to classify workers at the most detailed level possible.

[5]Kambourov and Manovskii (2002), using the PSID Retrospective Files, found industry-specific human capital to have a negligible role when occupation-specific human capital is taken into account. Poletaev and Robinson (2003) and Poletaev and Robinson (2004), using data for Canada and the U.S., found similar results using occupations or a set of basic skills associated with occupations.

[6]See for example Grossmann (2005) and Huggett et al. (2005).

[7]The Herfindahl index is obtained for each occupation by summing the squared shares of the occupation's

Similar to unemployment duration and wage loss, there is large variation on the concentration of occupational employment across industries. Some occupations, like financial records or handlers and laborers, have very low Herfindahl values and therefore low industry employment concentration, while occupations like teachers and construction laborers have their employment highly concentrated in few industries. Figure 4 graphs the Herfindahl values for all occupations in table 2. We can notice that even within major occupational groups, there is large variation in the concentration of occupational employment.

Aside from differences in the occupational employment distribution, variation in industries' employment fluctuations are also important to occupational employment 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 can greatly affect the portfolio of employment opportunities faced by each occupation. Figure 5 shows the average industry employment volatilities, including comovements, over the period 1979-2000 for aggregated industry classification codes.[8] We can see from this figure that there are large variations in volatility across industries.[9] For instance, industries like transportation, construction and services have much higher average volatility than manufacturing or utilities.

Figure 6 presents the shares of occupational employment across industries for four different occupations. The two top panels are examples of occupations with high employment concentration (Shoe Machine Operators in panel A and Assemblers in panel B), while the two bottom panels are examples of occupations with low employment concentration (Glaziers in panel C and Mechanics and Repairs in panel D). The occupations in panel A and C, however, are employed by a small number of industries while occupations in panels B and D are employed by almost all industries. We can see from this picture that although Assemblers are employed in all industries, more than 75% of its employment is concentrated in one industry (manufacturing, durable goods). At the same time, although Glaziers are employed by a small number of industries, their employment is more evenly distributed across the industries that employ them. Therefore, the number of industries employing an occupation does not necessarily determine how diversified occupational employment opportunities are; some occupations are employed in a large number of industries, but with its employment very concentrated in few of them, while others may have fewer industries employing them but with their employment more spread over

employment across all industries. This index is bounded between 0 and 1 and the higher is its value, the more concentrated the occupational employment is.

[8]This aggregated industry classification is used only for expositional purposes. In the estimation of the OER measure, I use 158 3-digit industry codes based on a match between the Census industry codes and the System of Industrial Classification (SIC). See appendix A.2 for details.

[9]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.

these industries. Moreover, the volatility occupational employment opportunities also depends on industry volatility. For instance, consider Shoe Machine Operators and Glaziers. At first glance, one may think that Glaziers would have more diversified employment than Shoe machine operators; however, the average volatility of the industries that employ Glaziers (from figure 5), is much higher than the volatility in the single industry that employs almost 98% of Shoe Machine operators. It is the combination of occupational employment concentration and volatility that determines the diversification of the portfolio of employment opportunities faced by each occupation.

Given the evidence above, I define and construct a measure of occupational employment risk (OER) which takes into account the concentration of occupational employment across industries and the volatility of industrial employment, including sectoral comovements. I estimate this measure 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 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.

This 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 depend on the diversification of occupational employment across industries and the level of industry employment volatility, including comovements. In a sense, 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. Nevertheless, a number of studies in the literature 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.[10], 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." Through the use of a similar measure, Shea (2002) finds that interindustry comovement is responsible for 95% of the variance of manufacturing employment.[11] Using 126 three-digit U.S. manufacturing industries over the 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 upon the fact that occupational employment is distributed differently across industries. Some occupations are employed in many industries, while others are only employed in a small number of industries. Meanwhile, 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 used in a larger number of industries may potentially 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) which 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 Neumann/Topel and Shea.

The concentration component of the OER measure is obtained by calculating the shares of occupational employment in each industry. I assume the shares to be in steady-state and compute them 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 am considering. The limitation of making such an assumption is that if the occupational employment shares are changing over time, my measure of OER would not capture these trends.[12] However, this issue is minimized by the fact that most of the trends in shares occur

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

[11]Shea estimates that the average pairwise correlation of annual employment growth is 0.34 and that, even after aggregating industries to 20 two-digit industries codes, comovement is still responsible for over 86% of manufacturing employment variation. For more on comovements, see Long and Plosser (1983) and Horvath (1998).

[12]Note that the steady-state assumption of the shares of occupational employment in each industry is not

at the three-digit occupational classification level, while I use a more aggregated occupational classification, which makes the shares more robust to changes over time. Nevertheless, as a robustness check, I also calculate the shares using the 1980 Census. Applying mean and variance comparison tests on the shares of occupational employment in each industry, I cannot reject the null hypothesis that 1980 and 1990 shares have the same mean and standard deviation.[13] I use 1990 shares since 1990 is the midpoint of my analysis. S_{vj} is the steady-state 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 in the 1990 Census and emp_v is the total employment in occupation v.

The volatility component, Ω_ε, is constructed using the variance-covariance matrix of disaggregated industry employment growth rates, ε_{jt}, $j = 1, ...J$ and time $t = 1978, ...2000$, which I estimate using data from the Quarterly Census of Employment and Wages (QCEW) over the period 1978 to 2000. In particular, note that Ω_ε incorporates not only the variance of industry employment but also the comovements among industries.[14] 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, MSA and county levels for the period 1975-2004.[15] The main limitation, however, is the change in industry codes over the time period available (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 through 1978-2000. I 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 may be found in the appendix at the end of the paper.[16]

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

necessarily inconsistent with the well-known phenomenon of skill upgrading within industries, as long as all industries are shedding less-skilled workers at the same rate.

[13]In fact, I have estimated two versions of OER, one using 1980 shares and another using 1990 shares, obtaining similar results.

[14]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.

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

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

the weights are the shares of occupational employment in each industry:[17]

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

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:

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

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 46 'detailed' occupational codes,[18] which is an intermediate occupational classification (between two and three-digit occupational codes) given by the Current Population Survey (CPS). There are two main advantages to using this classification. 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 closely related occupations. For example, a worker whose three-digit occupation is a 'Production, Planning, and Expediting Clerk' may also see himself as a 'Stock and Order Clerk' [19] and consider jobs in both positions. Second, a more aggregate classification reduces the problem of measurement errors from occupational misclassifications, which is an issue that normally affects longitudinal studies using occupations. Nevertheless, the detailed occupational code (from now on referred as DOC), is still quite a rich classification, with three times as many occupational categories as the two-digit code.

Figure 7 presents estimates of the OER measure for different occupations. One can see that there is a large variation in this measure of occupation employment risk across occupations, even within major occupational groups. Figure 8 shows the change in average hourly pay upon reemployment by OER measure and occupational mobility groups. Unemployed workers in high OER occupations have on average 1.31 percentage point higher wage loss if they switch occupations and a 2.32 percentage point wage gain (instead of a 1% wage loss) if they remain in the same occupation, in comparison with workers in low OER occupations. The right panel

[17] This assumption, however, would not be robust to deskilling, even if deskilling was uniform across industries.

[18] See appendix A.2 for a description.

[19] Both of these occupations are classified as being closely related by the Occupational Outlook Handbook published by the Bureau of Labor Statistics (BLS).

of figure 8 shows the same graph for displaced workers. The results are similar. High OER occupational stayers have a 5.97% gain in wages, while low OER occupational stayers face a 3.50% wage loss. Although the gap among occupational switchers is smaller for high and low OER occupations, the former has a 0.78 percentage point higher hourly wage loss than the latter.[20]

3 OER Measure and Unemployment Duration

In this section, I estimate the effect of OER on the hazard rate of leaving unemployment and, subsequently, 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, since they can still retain, and therefore capitalize on their occupation-specific human capital. This suggests that it is important to distinguish between two exit modes out of unemployment: finding a job in the same or in a different occupation. In order to accomplish this, I use a continuous-time competing risk model, which I estimate by using a Cox Proportional Hazard model with multiple spells and time-varying covariates.

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, $h_0(t)$.[21] 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. Wrong assumptions on the shape of $h_0(t)$ would produce incorrect results regarding how the covariates affect the hazard. The only assumption made concerning the shape of $h_0(t)$ is that it is the same for everyone.[22] 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 ith 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

[20]The correlation between the OER measure and wage loss is -0.17, while the correlation between the OER measure and the average unemployment duration is 0.20.

[21]Cox (1972) proposed 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.

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

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 which 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, obtained by following the two-step methodology presented by Cawley et al. (1995) and Kermit et al. (1997). The appendix at the end of the paper provides details.[23] $Z_i(t)$ 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[24].

Construction of the Panel

I restrict the sample to unemployment spells whose duration was less than 53 weeks in occupations for which there were at least 20 observations. I make these restrictions to obtain more reliable estimates, by reducing classical measurement error in the data and by not including possibly discouraged workers.[25] In order to exclude the period of high job turnover at the beginning of individuals' careers, I further restrict the sample by considering only spells in which the individual was at least 21 years old at the beginning of the spell (see Neal (1995)). Moreover, I consider only completed spells, which I define to be a transition from employment to unemployment and then back to employment again, except for the last spell in the sample which may be censored.[26] The duration of a spell is the difference in weeks between the end and the beginning of the spell.

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.[27] This paper uses

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

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

[25] Out of the 45 detailed occupational codes, there were 16 codes for which there were less than ten observations, representing 1.4% of the spells. Unemployment spells with a duration of more than 52 weeks were less than 2% of the sample.

[26] A worker is considered to be 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.

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

the unbalanced panel of civilian males, covering 1979-2000, which contains 5,579 individuals. I restrict the sample to males in order to avoid labor force participation issues that arise when including women in the sample.

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

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.[28] 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 U.S. 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 either estimate the expected length of spell duration for a synthetic cohort of individuals entering unemployment (using continuation rates) or estimate the average completed spell length for the currently unemployed workers by 'doubling' the average duration of their spells.[29] 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.[30] In addition to the advantages mentioned above, the NLSY79 also has ability measures and lower attrition rates than other longitudinal data sets, such as the Panel Study of Income Dynamics (PSID). The downside of using the NLSY79 instead of the CPS is that I am able to analyze only individuals of a specific cohort, which is still relatively young. In 2000, the individuals' age range was 35 to 43 years old.

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

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

[29]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.

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

reports up to five employers.[31] 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 and further to the weekly work history files.[32] 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. This panel allows me to obtain good measures of work experience and tenure within given employer, which I calculate weekly by accumulating the number of weeks reported working and working for a particular employer, respectively.

Issues that normally arise with the use of occupational codes (and to a less 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 occupation 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 combines closely related occupations, but which 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 mode 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, 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.[33]

Table 3 shows the basic characteristics of the sample, with the last two columns referring to the subsamples of occupational stayers and switchers. One can see from this table that around 44% of unemployment spells ended in occupational mobility and that workers who switched occupations seem to be different from workers who remained in the same occupation. In comparison to workers who switched, a larger fraction of stayers are white, single, have college

[31] 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 one percent of those interviewed.

[32] 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 which jointly taken indicate, for every current survey employer the job number it received in the previous survey and whether it is a new job.

[33] I thank Audrey Light for pointing out the significant amount of occupation miscoding within employers in the NLSY79 data. Neal (1999) assumes each employer's industry and occupational codes to be the first one ever reported.

degree, have more experience and tenure, and report having used unemployment insurance. In addition, more occupational switchers reported having been displaced than occupational stayers.

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 hazard of leaving unemployment for a one-unit change in the corresponding covariate. 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%. Translating, a one standard deviation increase in OER represents a 5.1% decrease in the hazard of finding a job in every week of unemployment. All else, a worker in a high risk occupation, as defined by the OER measure, faces a longer unemployment spell than a worker in a low risk OER occupation. The OER measure has no effect on the hazard of leaving unemployment to a job in a different occupation, however.

I also find that being white increases the hazard of leaving unemployment to a job in the same occupation by 42%, but has no effect on leaving unemployment to a job in a different occupation. In comparison with high school dropouts, workers with a college degree have a 56.7% lower hazard rate of getting a job in the same occupation and a 6.5% lower hazard getting a job in a different occupation, although the latter result is not statistically significant.

An extra year of experience and tenure increases the hazard of leaving unemployment to a job in the same occupation by 6.24% and 20.57%, respectively, while it decreases the hazard of leaving for a job in a different occupation by 5.08% and 13.30%. Having received unemployment insurance increases by 24.1% the hazard of leaving unemployment to a job in the same occupation, while it decreases by 28.4% 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 this section, I examine more formally how the OER measure relates to wage losses. Evidence shown in section two suggests that unemployed workers in high OER occupations have 1.31

percentage point greater wage losses if they switch occupations, in comparison with workers in low OER occupations.

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 post- and pre-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:

$$\Delta lnw = \beta_0 + \beta_1 OER + \beta_2 X + \beta_3 Z + \beta_4 slength + \epsilon \tag{6}$$

X and Z are the same matrices of covariates used to estimate the effects of OER on the hazard rate of leaving unemployment. *slength* is the total weeks of unemployment, which I expect to have a negative estimated coefficient, given that workers tend to lower their reservation wage as their unemployment spell length increases. All the other covariates refer to pre-unemployment values.

I run this regression for three different samples: occupation stayers, occupational switchers and the full sample. Given the empirical evidence shown above, I expect OER to have negative estimated coefficients. 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. This effect is statistically significant for occupational switchers and for the full sample. In particular, a one-unit increase in the OER measure increase the hourly wage loss by 4.88% for all workers and 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. Similarly, an extra year of tenure increase 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 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 which has not been examined before and which seems to have an important role in explaining observable differences in unemployment duration and wage losses across occupations. I argue that this risk arises from the 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 the individuals employed in these occupations potentially face lower unemployment risk than individuals employed in occupations with less diversification.

Using data from the 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 loss 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 to 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 affects their employment duration and incidence of unemployment.[34] 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.

The type of risk documented and analyzed in this paper may affect the occupational and career choice 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 search strategy of unemployed individuals, it is worth noting that OER is closely related to the trade off between accepting a job today or waiting for a better offer tomorrow. As shown in the 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 risk affects precautionary savings. This should have implications on wealth holdings and consumption behavior. In the context of

[34] Preliminary exploration of this issue indicates that workers in high OER measure occupations receive wage compensating differentials and have longer employment spells than workers on low OER occupations.

a life cycle model, the type of risk implied by occupational employment diversification would affect the transition matrix between being employed/unemployed, 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.

6 Appendix

A.1 Weekly Labor Status

The NLSY79 Work History Data provides 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 not working since the date of the last interview.[35] Since the questions in the NLSY survey are constructed to collect a complete history for each respondent, regardless of period of non-interview, it is possible to construct for each respondent, a continuous, week-by-week labor force status record.[36] 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 employment gaps. "Split gaps" occur during an employment gap in which individuals report being unemployed for part of the gap and out of the labor force for the other part of it.[37]. 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.

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

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

[36] 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 Documentation Files.

[37] 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 in "split gaps," see Appendix 18 in the NLSY documentation.

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

About 1% of the weeks in the male, not military sample, have wk 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 which assumes the values:[38]

$$empstat = \begin{cases} 1 & \text{if wk} = 3 \text{ or wk}>7; \\ 2 & \text{if wk} = 4 \text{ or } (\text{wk}_t{=}2)\&(2 \leq \text{wk}_{t-1} \leq 4) \text{ or } (\text{wk}_t{=}2)\&(\text{wk}_{t-1} > 7); \\ 3 & \text{if empstat} \neq \ 1 \ \mathit{or} \ 2; \end{cases}$$

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 one of them has a unique combination of inputs and outputs, production techniques, occupations, and business characteristics. Occupations are classified based upon 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 are individuals age sixteen or older who worked within the previous five years and are not considered new workers.[39] 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, if the respondent was not sure about their income, his/her primary occupation and industry was then the ones at which s/he spent the most time. If a person listed more than one occupation

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

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

and/or industry, the samples use the first one listed. The occupational codes were assigned based in the questions: (1) what kind of work was this person doing? and (2) what were this person's most important activities or duties? While the industry codes were assigned based in 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 or, wholesale trade, or retail trade or other?

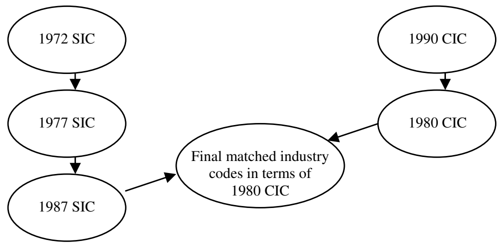
Matching Industry Codes

In order to estimate the OER measure, I calculate the concentration of occupational employment across industries and the volatility and comovement of disaggregated industry 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 Quartely 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 System (SIC). So 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 by 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 of this appendix.

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 existent one; and (3) new industry codes due to a new industry in the economy. The changes between the Census 1980 and 1990 Industry Classification Systems were minimal and the criteria I use to deal with them can be summarized by using the correspondent 1980 code for changes of type (1), 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 the type (3).

Figure A.3: Industry codes' matching



The QCEW data uses 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 SIC and 1977 SIC and between the 1977 SIC to 1987 SIC. Based in 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 Industry Classification codes, I use a Census crosswalk between 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. [40] After the matches, I obtain 158 industry codes, which constitutes a 33% reduction from the number of 3-digit industries in 1980 and 1990 CIC codes. Figure A.3 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 existent industry codes, resulting in the creation of a new code or 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

[40]See Census technical paper #65.

single code for changes of type (2).

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 uses the 1970 Census occupational codes in reporting the occupations for up to five jobs each individual held during any survey round.[41] 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 provides, for each occupation, a quantification of the employment relationship between these two systems, which I use in generating the correspondences between them. The criterion I use is to assign, for each 1970 occupational code, the 1980 occupational code that received the largest share of the 1970 occupational code's employment. Over 76% of all occupations in the 1970 code had over 75% of its employment going to a single occupation code in 1980.[42]

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), which is 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) mathematic 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. (1997), 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 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 square residuals from these regressions. See Heckman (1995) on using the

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

[42] Around 40% of all occupations in the 1970 code had over 99% of its employment going to a single occupation code in 1980, while 86% had over 50% of its employment going 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.3 : 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		
Mathematics knowledge residuals	0.31038	0.23927		
Mechanical comprehension residuals	0.32052	-0.28386		
Electrical Information residuals	0.32958	-0.31302		

first two principal components and Kermit et al. (1997) for an application of this procedure. The estimates are presented in table A.3.

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Table 1: Average Unemployment Duration and Wage Change by Occupation

(CPS) Detailed Occupation Title	Duration	Std. Err.	Wage Change	Std. Err.
Executive, Administrators, and Managers, exc. Pub. Adm.	12.31	(1.04)	-0.06	(0.04)
Management Related Occupations	15.49	(2.75)	-0.06	(0.06)
Engineers	10.52	(2.00)	-0.16	(0.11)
Teachers, Except College and University	6.33	(1.23)	-0.07	(0.07)
Other Professional Specialty Occupations	10.79	(1.09)	0.11	(0.07)
Engineering and Science Technicians	13.19	(1.85)	-0.05	(0.07)
Technicians, Except Health Engineering, and Science	7.85	(1.62)	0.14	(0.06)
Sales Representatives, Finance, and Business Service	12.58	(2.45)	-0.02	(0.05)
Sales Representatives, Commodities, Except Retail	12.56	(1.43)	-0.17	(0.05)
Sales Workers, Retail and Personal Services	15.93	(2.28)	0.03	(0.07)
Financial Records, Processing Occupations	7.61	(2.30)	0.01	(0.04)
Mail and Message Distributing	11.75	(2.25)	0.04	(0.02)
Other Administrative Support Occupations, Including Clerical	11.21	(0.98)	0.01	(0.04)
Protective Service Occupations	15.28	(2.38)	-0.07	(0.05)
Food Service Occupations	13.24	(1.01)	0.01	(0.03)
Health Service Occupations	13.41	(2.42)	0.00	(0.03)
Cleaning and Building Service Occupations	18.10	(1.77)	0.05	(0.04)
Personal Service Occupations	17.26	(5.05)	-0.06	(0.07)
Mechanics and Repairers	12.95	(0.98)	0.00	(0.03)
Construction Trades	11.88	(0.68)	0.01	(0.02)
Other Precision Production Occupations	13.30	(1.13)	-0.01	(0.03)
Machine Operators and Tenders, Except Precision	12.18	(0.98)	-0.02	(0.02)
Fabricators, Assemblers, Inspectors, and Samplers	11.54	(0.91)	0.02	(0.02)
Motor Vehicle Operators	12.35	(1.04)	0.01	(0.04)
Other Transportation Occupations and Material Moving	13.20	(1.25)	-0.02	(0.02)
Construction Laborer	11.87	(0.73)	0.01	(0.03)
Freight, Stock and Material Handlers	14.10	(1.26)	-0.02	(0.04)
Other Handlers, Equipment Cleaners, and Laborers	14.05	(1.11)	0.02	(0.04)
Farm Workers and Related Occupations	14.59	(0.97)	0.03	(0.04)
Forestry and Fishing Occupations	8.48	(1.77)	0.15	(0.10)
Overall	12.53	(0.87)	-0.01	(0.02)
Number of spells	6246		3619	
Number of clusters	2216		1778	

Table 2. Measure of occupational employment concentration: Herfindahl-Index

(CPS) Detailed Occupation Title	Herfindahl Index
Public Administration	0.162
Other Executive, Administrators, and Managers	0.035
Management Related Occupations	0.046
Engineers	0.103
Mathematical and Computer Scientists	0.065
Natural Scientists	0.076
Health Diagnosing Occupations	0.461
Health Assessment and Treating Occupations	0.421
Teachers, College and University	0.951
Teachers, Except College and University	0.720
Lawyers and Judges	0.580
Other Professional Specialty Occupations	0.054
Health Technologists and Technicians	0.346
Engineering and Science Technicians	0.073
Technicians, Exc. Health, Engineering, and Science	0.045
Supervisors and Proprietors, Sales Occupations	0.065
Sales Representatives, Finance, and Business Service	0.348
Sales Representatives, Commodities, Exc Retail	0.089
Sales Workers, Retail and Personal Services	0.083
Sales Related Occupations	0.125
Supervisors - Administrative Support	0.042
Computer Equipment Operators	0.034
Secretaries, Stenographers, and Typists	0.038
Financial Records, Processing Occupations	0.027
Mail and Message Distributing	0.454
Other Adm. Support Occupations, Incl. Clerical	0.035
Private Household Service Occupations	1.000
Protective Service Occupations	0.343
Food Service Occupations	0.505
Health Service Occupations	0.257
Cleaning and Building Service Occupations	0.079
Personal Service Occupations	0.190
Mechanics and Repairers	0.054
Construction Trades	0.551
Other Precision Production Occupations	0.105
Machine Operators and Tenders, Except Precision	0.067
Fabricators, Assemblers, Inspectors, and Samplers	0.115
Motor Vehicle Operators	0.106
Other Transportation Occupations and Material Moving	0.090
Construction Laborer	0.833
Freight, Stock and Material Handlers	0.157
Other Handlers, Equipment Cleaners, and Laborers	0.028
Farm Operators and Managers	0.474
Farm Workers and Related Occupations	0.205
Forestry and Fishing Occupations	0.309

Table 3: Sample Statistics

Variables	All sample	Stayers	Switchers
Age	28.07	27.52	26.61
	(0.11)	(0.24)	(0.17)
White	79.81%	84.27%	76.53%
Married	44.92%	40.52%	51.94%
Years Schooling	12.13	11.82	12.00
	(0.06)	(0.10)	(0.11)
HS	70.52%	72.56%	68.91%
College	8.03%	3.92%	7.07%
Experience	4.98	4.65	3.79
	(0.10)	(0.21)	(0.14)
Tenure	1.34	1.63	0.87
	(0.07)	(0.18)	(0.05)
Received UI	41.77%	56.08%	34.36%
Displaced	19.99%	14.13%	24.28%
Number of spells	5344	1460	1143
N. of clusters	2216	743	738

Note: (1) Standard deviations are in parentheses; (2) There are 2,741 unemployment spells for which no occupational code was reported either for the previous or the new job.

Table 4. Unemployment Duration: Cox PH Estimated Hazards

	Same Occupation		Different Occupation	
	coef.	std	coef.	std
OER	0.746	(0.125)†*	0.997	(0.196)
White	1.423	(0.131)**	0.998	(0.087)
Age	0.788	(0.148)	1.102	(0.245)
Age^2	1.004	(0.003)	0.997	(0.004)
Ability Factor 1	1.028	(0.021)	1.013	(0.018)
Ability Factor 1^2	0.996	(0.006)	0.998	(0.005)
Ability Factor 2	0.996	(0.006)	0.935	(0.043)
Ability Factor 2^2	1.016	(0.030)	0.977	(0.032)
High school	1.034	(0.099)	1.010	(0.091)
College	0.433	(0.127)**	0.914	(0.162)
Married	0.923	(0.072)	1.032	(0.084)
Experience	1.134	(0.070)*	1.063	(0.076)
Experience^2	0.993	(0.004)†	0.999	(0.006)
Tenure	1.235	(0.064)**	0.832	(0.063)*
Tenure^2	0.989	(0.005)*	1.013	(0.011)
Unemp. Ins.	1.241	(0.095)**	0.716	(0.058)**
Unemp. Rate	0.999	(0.016)	0.973	(0.013)*
N. of spells	11019		11019	
N. of clusters	2035		2035	
Wald chi2(17)	118.51		47.28	

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

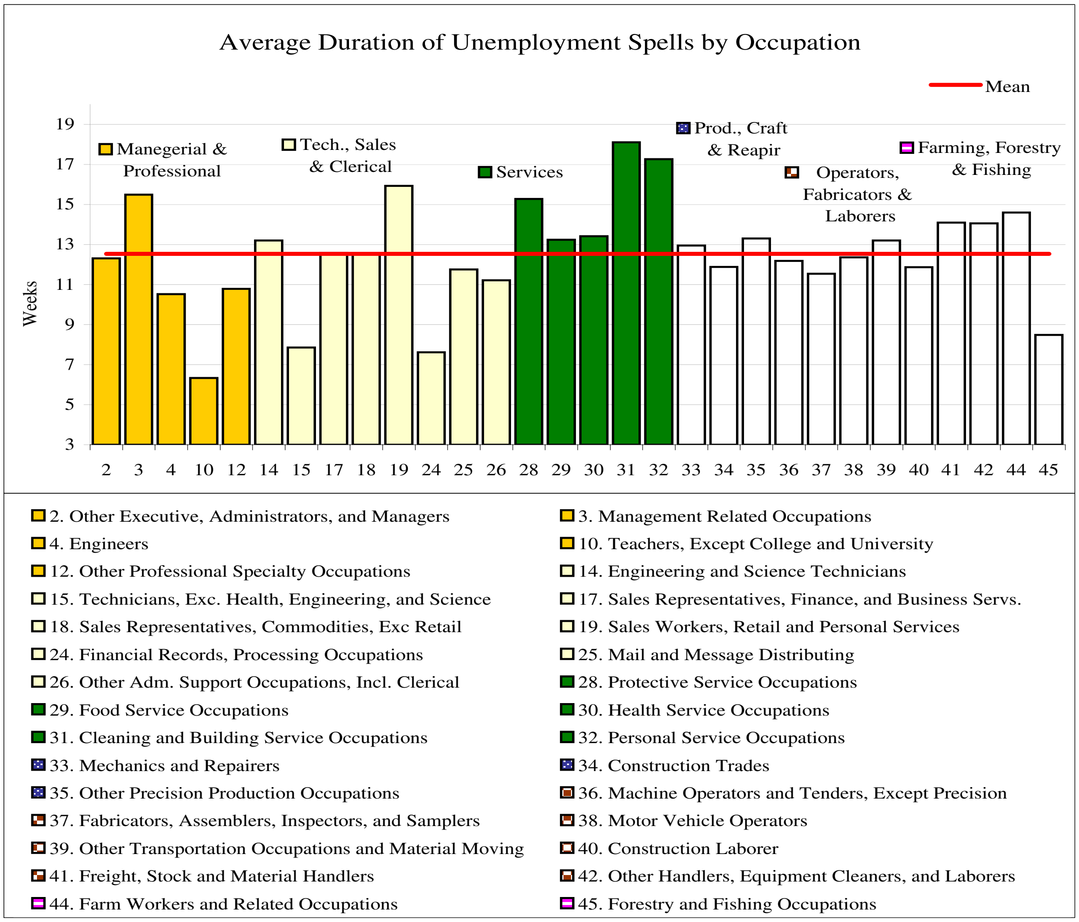
Table 5. Wage Change: OLS estimates

	All sample		Stayers		Switchers	
	coef.	std	coef.	std	coef.	std
OER	-0.0488	(0.0351)†	-0.0051	(0.0502)	-0.1145	(0.0541)*
White	-0.0145	(0.0151)	-0.0132	(0.0156)	-0.0233	(0.0359)
Age	-0.0154	(0.0284)	-0.0133	(0.0276)	-0.0247	(0.0652)
Age^2	0.0003	(0.0005)	0.0002	(0.0005)	0.0004	(0.0011)
Ability Factor 1	0.0033	(0.0037)	0.0036	(0.0037)	0.0029	(0.0087)
Ability Factor 1^2	0.0005	(0.0011)	-0.0003	(0.0012)	0.0025	(0.0024)
Ability Factor 2	0.0151	(0.0074)*	0.0177	(0.0078)*	0.0134	(0.0154)
Ability Factor 2^2	0.0050	(0.0064)*	0.0075	(0.0049)*	0.0034	(0.0098)
High School	0.0070	(0.0182)	-0.0044	(0.0164)	0.0373	(0.0453)
College	-0.0345	(0.0395)	-0.0021	(0.0467)	-0.0574	(0.0689)
Married	0.0180	(0.0151)	-0.0045	(0.0156)	0.0644	(0.0328)†
Experience	-0.0033	(0.0100)	-0.0021	(0.0088)	0.0201	(0.0228)
$Experience^2$	-7.04e-06	(0.00002)	4.84e-07	(0.00001)	-0.00003	(0.00003)
Tenure	-0.0211	(0.0083)*	-0.0112	(0.0075)	-0.0617	(0.0268)*
$Tenure^2$	0.00004	(0.00001)*	0.00002	(0.00001)	0.0001	(0.0001)*
Spell length	-0.0014	(0.0005)**	-0.0018	(0.0006)**	-0.0009	(0.0008)
constant	0.2356	(0.3943)	0.2432	(0.3786)	0.2942	(0.9149)
Number of spells	3462		2212		1250	
Number of clusters	1691		1246		884	
F-Test	1.78		1.30		1.71	
Prob > F	0.0290		0.1864		0.0390	
R-squared	0.0112		0.0127		0.0248	

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

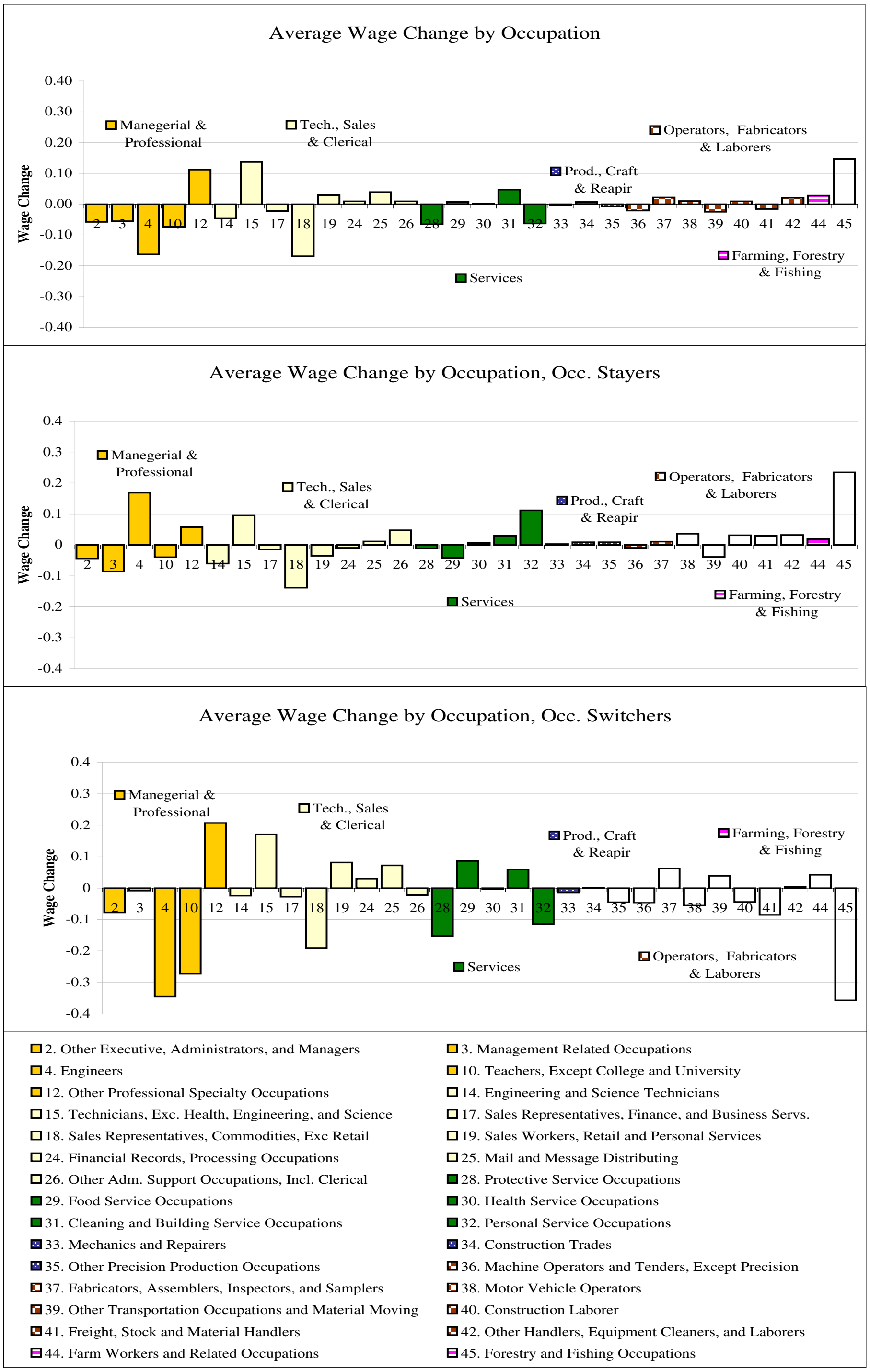
Note: (1) Standard deviations are in parentheses; (2) Ability factors 1 and 2 are the first two principal components of the age-adjusted ASVAB scores.

Figure 1: Average unemployment duration by occupation



Source: NLSY79, 1979-2000.
*Occupations with less than twenty observations are omitted from the analysis.

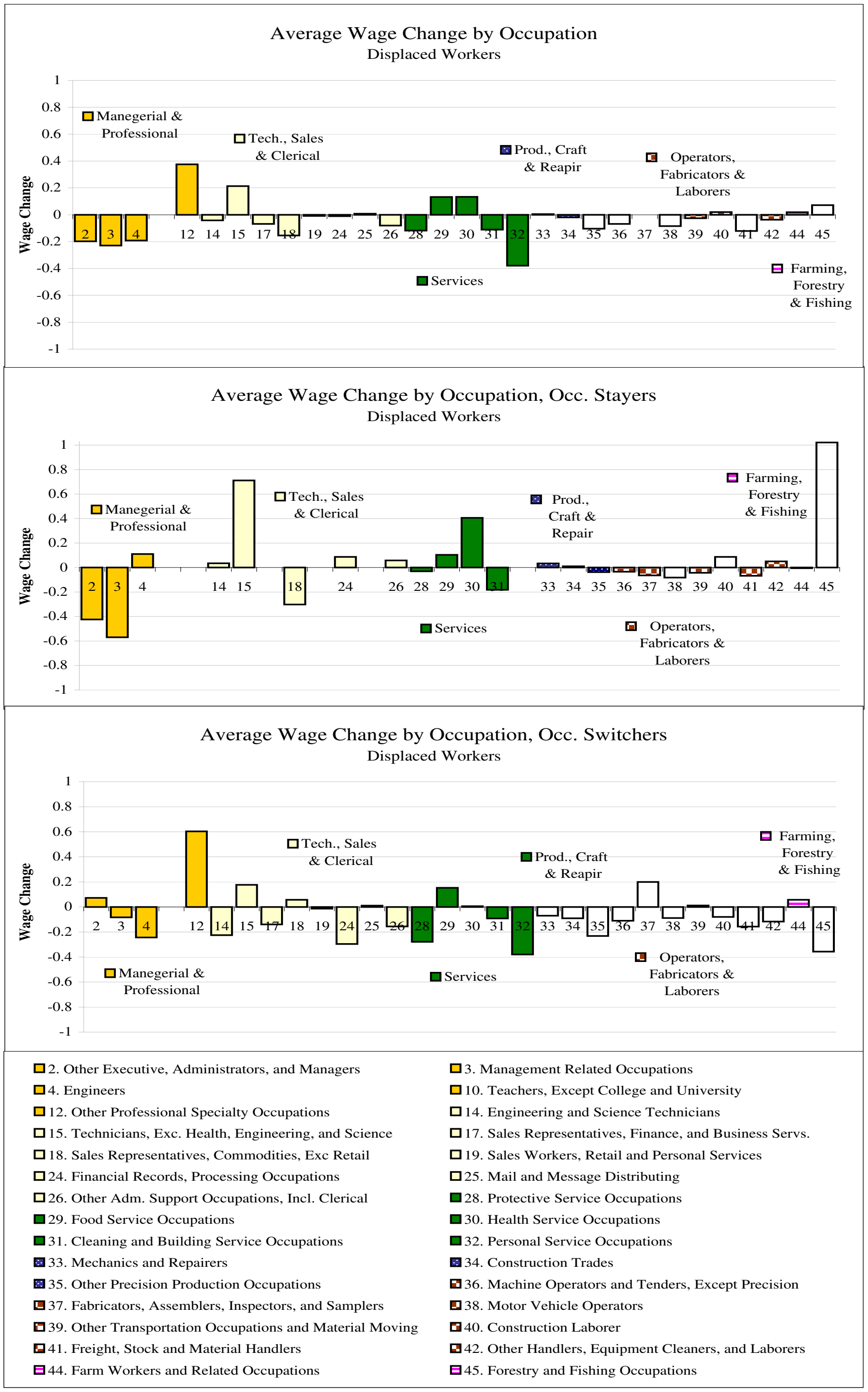
Figure 2: Average wage change across occupation



Source: NLSY79, 1979-2000.

*Occupations with less than twenty observations are omitted from the analysis.

Figure 3: Average wage change across occupation, displaced workers

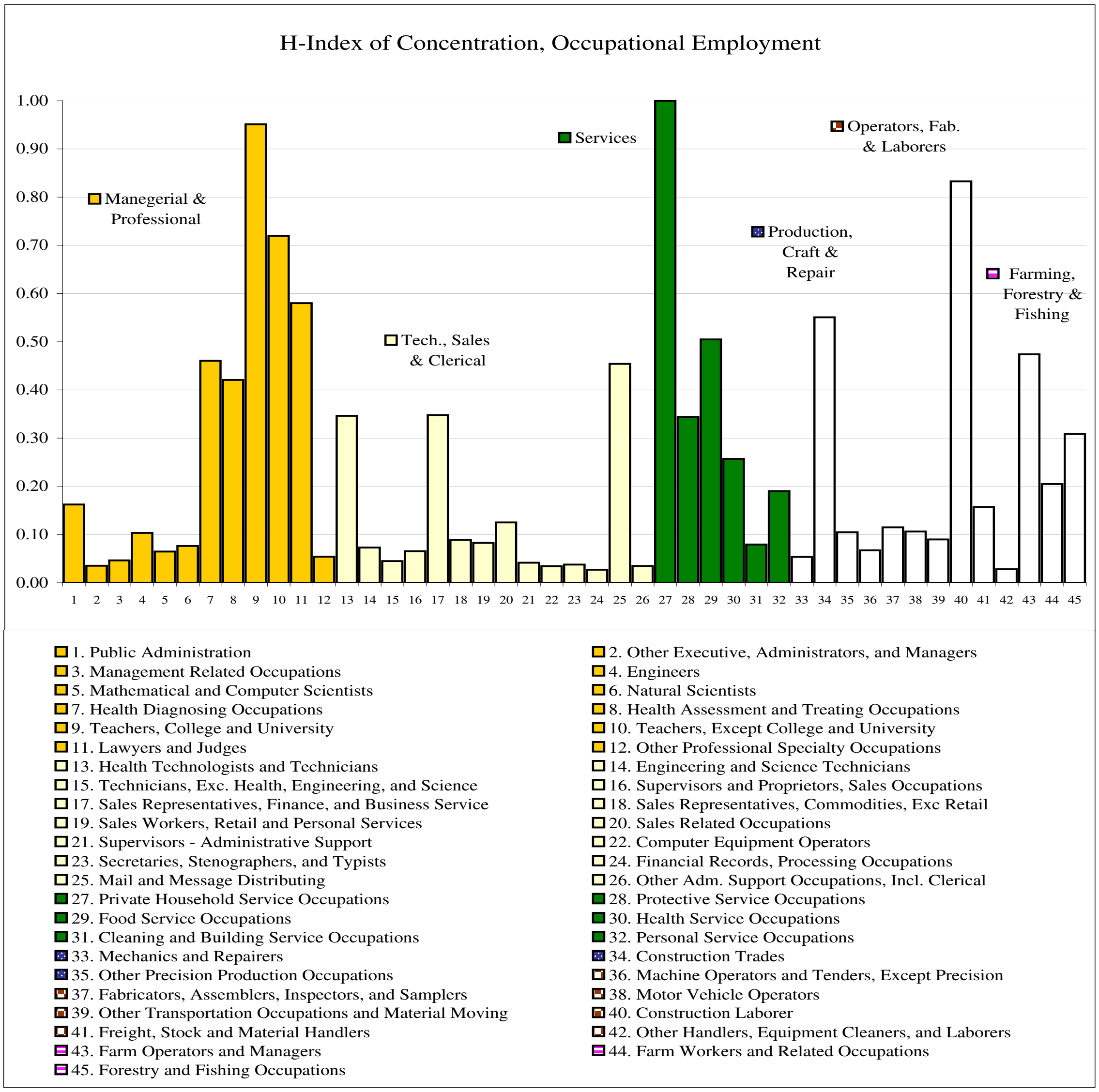


Source: NLSY79, 1979-2000.

*Occupations with less than twenty observations are omitted from the analysis.

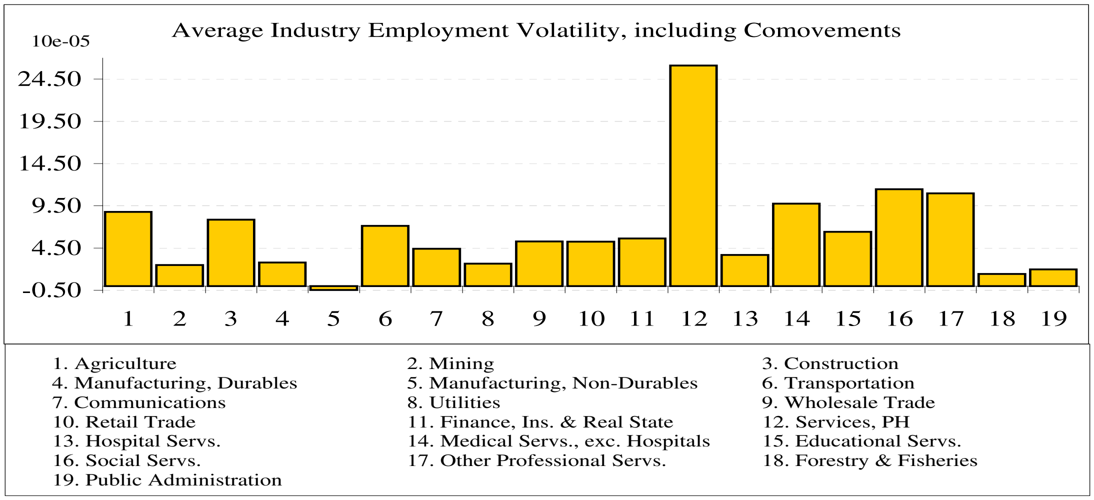
** There are no displaced workers on occupation 10 and no occupational stayers-displaced workers in occupations 12, 17, 19, 25 and 32.

Figure 4: Concentration measure for occupational employment



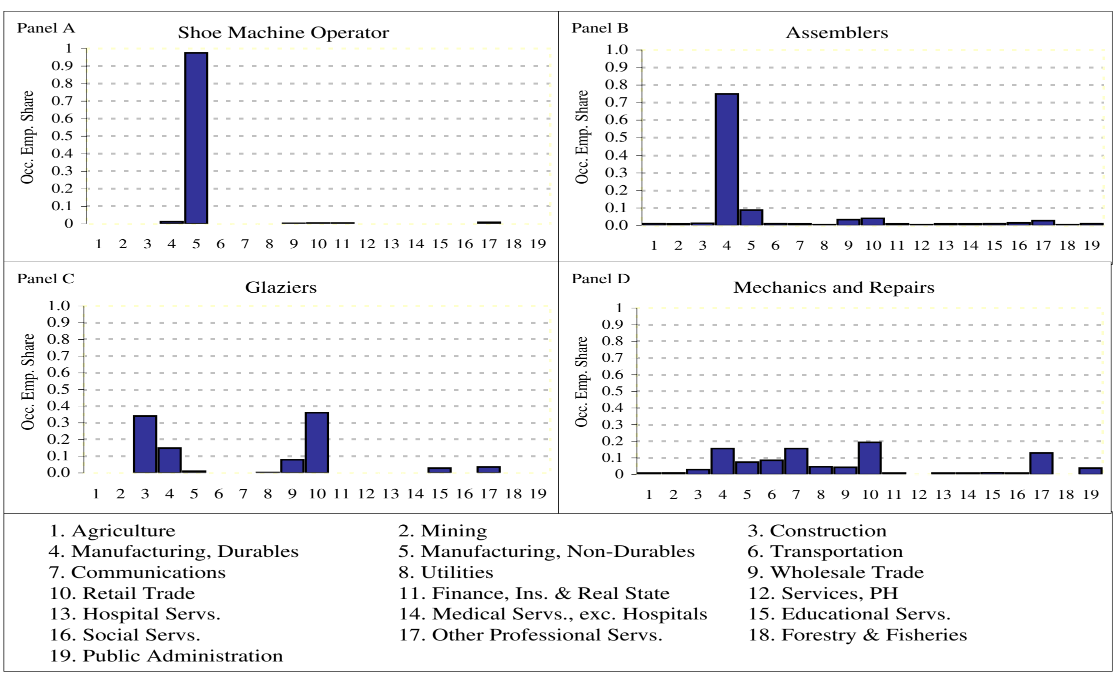
Source: 1990 Census & QCEW 1979-2000.

Figure 5: Differences in industry employment volatility across occupations



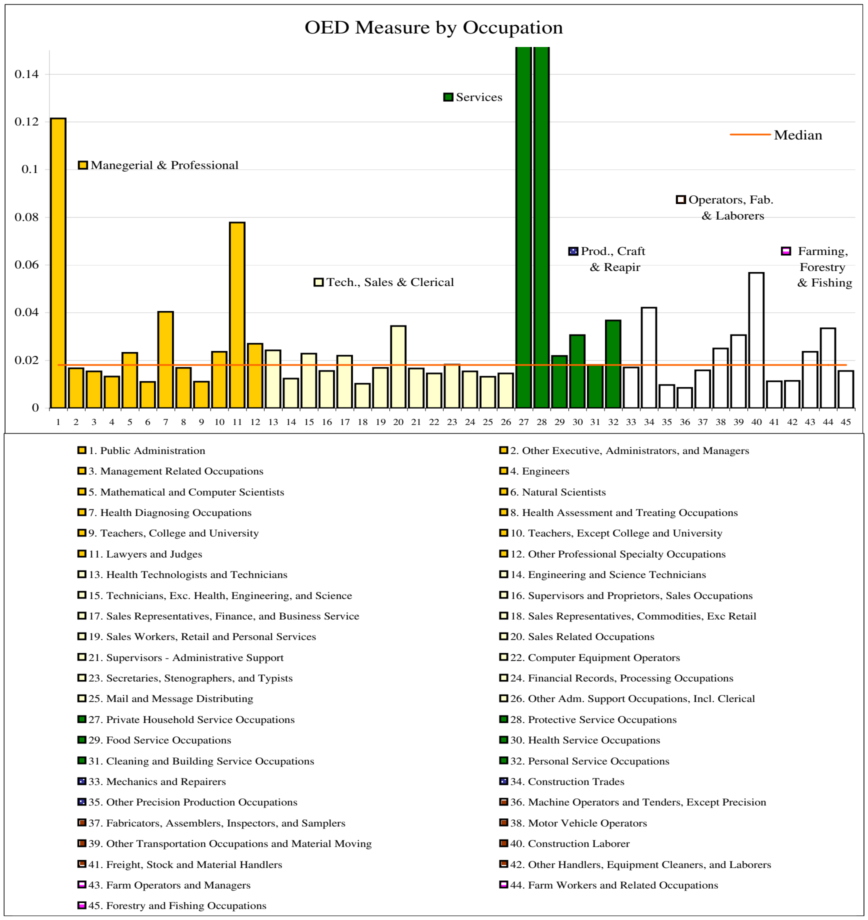
Source: QCEW, 1979-2000.

Figure 6: Differences in the concentration of occupational employment across industries



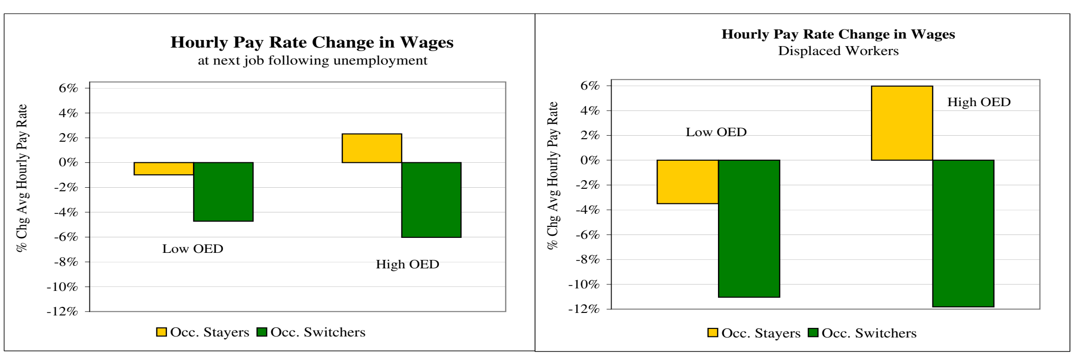
Source: 1990 Census.

Figure 7: Occupational employment diversification



*OED for occupation 28 is 1.15, truncated at 0.35 for better graphical visualization.
Source: 1990 Census & QCEW 1979-2000.

Figure 8: Wage Change by OER and occupational mobility



Source: NLSY79, 1979-2000.
*Displaced Workers are workers that report losing their jobs due to layoff or plant closing.
** Occupational stayers are unemployed workers who become reemployed in the same occupation.
Conversely, occupational switchers are unemployed workers who become reemployed in a different occupation.
*** In the graphs, low OED occupations are the ones for which OED measure is below the bottom 10 percentile, while high OED occupations are the ones on the top 10 percentile.