Occupational Mobility and Wage Inequality*

Gueorgui Kambourov[†]
University of Toronto

Iourii Manovskii[‡]
University of Pennsylvania

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Abstract

In this study we argue that wage inequality and occupational mobility are intimately related. We are motivated by our empirical findings that human capital is occupation-specific and that the fraction of workers switching occupations in the United States was as high as 16% a year in the early 1970s and had increased to 21% by the mid 1990s. We develop a general equilibrium model with occupation-specific human capital and heterogeneous experience levels within occupations. We find that the model, calibrated to match the level of occupational mobility in the 1970s, accounts quite well for the level of (within-group) wage inequality in that period. Next, we find that the model, calibrated to match the increase in occupational mobility, accounts for over 90% of the increase in wage inequality between the 1970s and 1990s. The theory is also quantitatively consistent with the level and increase in the transitory variability of earnings.

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†Department of Economics, University of Toronto, St. George St., Toronto, ON, M5S 3G7 Canada. E-mail: g.kambourov@utoronto.ca.

‡Department of Economics, University of Pennsylvania, 160 McNeil Building, 3718 Locust Walk, Philadelphia, PA, 19104-6297 USA. E-mail: manovski@econ.upenn.edu.

1 Introduction

Despite an active search for the reasons behind the large increase in wage inequality in the United States over the last 30 years, identifying the culprit has proved elusive. In this paper we suggest that the increase in the variability of productivity shocks to occupations, coupled with the endogenous response of workers to this change, can account for most of the increase in wage inequality.

Several facts, documented in detail in Section 2, characterize the changes in wage inequality in the U.S. from the early 1970s to the early 1990s.

1. Inequality of hourly wages as measured by the Gini coefficient has increased by 6.6 Gini points, or 25%.

2. Over half of the increase in wage inequality was due to rising inequality within narrowly defined age-education subgroups.

3. The increase in wage inequality reflects increased dispersion in all parts of the wage distribution: real wages at the bottom of the distribution fell, and wages at the top increased.

4. Individual earnings became substantially more volatile.

We document below that there was a considerable increase in the fraction of workers switching occupations (e.g., cook, accountant, chemical engineer) over the same period. The increase is pronounced for switches defined on all one-, two-, and three-digit U.S. Census Occupational Classifications.

The link between occupational mobility and wage inequality is motivated by our finding that human capital is specific to the occupation in which an individual works. We show that occupational experience is considerably more important in determining wages than either industry or employer tenure. This is intuitive: one would expect the human capital loss of a truck driver who loses a job in some food industry and finds another one in the furniture industry to be lower than the loss of a truck driver who becomes a cook.

Occupational mobility and wage inequality are interrelated because occupational mobility affects the distribution of occupational tenure and, thus, of human capital. In addition, different occupations are characterized at a point in time by different levels of demand or different productivity levels. Thus, in addition to the distribution of occupational tenure in the population, wage inequality depends on the distribution of workers across occupations. To evaluate the connection between occupational mobility and wage inequality, one needs an empirically grounded general equilibrium model in which occupational mobility and wage inequality are endogenously determined.

The model we develop is based on the equilibrium search framework of Lucas and Prescott (1974) (see Alvarez and Veracierto (2000) for an important recent extension and application). In that model, agents can move between spatially separated local labor markets that the authors refer to as "islands," and, although each local market is competitive, there are frictions in moving between locations. Here we do not adopt this spatial interpretation, but think of "islands" as occupations. Further, we introduce a heterogeneity of workers with respect to their occupational experience levels and allow for occupation-specific human capital. Thus, when an individual enters an occupation, she has no occupation-specific experience. Then, given that she remains in that occupation, her level of experience increases over time. When an individual switches her occupation, she loses the experience accumulated in her previous occupation. Output and wages in each occupation are a function of the employed amount of effective labor. Occupations are subject to idiosyncratic productivity shocks. We argue that the variability of these shocks has increased from the early 1970s to the early 1990s.

We quantify the effects of the increased variability of the occupational productivity shocks in the following experiment. We calibrate the parameters of the model to match a number of observations for the early 1970s. Next, keeping the rest of the parameters fixed, we recalibrate the parameters governing the variability of the productivity shocks to occupations in order to match several facts on occupational mobility for the early 1990s. At no point in the calibration do we target wage inequality.

The results imply that the calibrated model accounts for over 90% of the increase in wage inequality, the decline in wage stability, and it is consistent with the other facts mentioned above. We find that, in order to match the calibration targets, the variance of productivity shocks to occupations must have increased substantially, while the persistence of the shocks must have declined. An important question is whether the endogenous increase in occupational mobility tends to increase or decrease the change in wage inequality. When only the variance of productivity shocks increases, wage inequality immediately increases if workers do not adjust their behavior. However, once workers are allowed to reallocate from less productive to more productive occupations, this endogenous response dampens the increase in inequality. When the persistence of productivity shocks declines as well, search becomes less attractive because high productivity realizations are shorter-lived. Since switching occupations involves destruction of human capital, more workers choose to remain on temporarily less productive occupations. These changes in workers' behavior strongly amplify the effect of the increase in the variability of productivity shocks to occupations on wage inequality.

The assumption that occupations experience idiosyncratic productivity shocks is not controversial. The occupational mix varies substantially over time. New occupations arise and old ones disappear. This process depends on many factors, such as changes in technology, international trade, the demographic composition of the population, government regulations, and labor market institutions. Many occupations exhibit substantial changes in their sizes over time (see Kaboski (2000)). One of the many examples that come to mind is the experience of typesetters in the late 1970s - early 1980s. Many of these highly skilled workers had to switch occupations with the advent of computerized typesetting. Needless to say, they started in their new occupations as inexperienced, relatively low-paid workers.

A number of papers, including Bertola and Ichino (1995) and Ljungqvist and Sargent (1998), have argued that the economy became more turbulent between the 1970s and 1980s. Turbulence is typically defined as an unobservable increase in the rate of skill depreciation upon a job switch over the period. Despite the intuitive appeal of the notion of increased economic turbulence, identifying it in the data has proved difficult. We suggest that an observable increase in occupational mobility serves as a measurable manifestation of the increased turbulence. We identify the increase in turbulence with the increased variability of the occupational productivity shocks.

Most of the research on the increase in wage inequality was concentrated on explaining the rise in the college premium (e.g., Krusell, Ohanian, Ríos-Rull, and Violante (2000)). The increase in the college premium, however, accounts for about a third of the overall increase in inequality. A distinguishing feature of this paper is that it provides a theory of within-group inequality. In essence, we argue that a substantial part of the variance of wages for individuals from the same age-education group is explained by the heterogeneity of their occupational experience and by the current level of demand for the services of the occupations in which these workers choose to be employed.

The existing theories of within-group inequality mainly rely on ex-ante differences in workers' abilities (e.g., Caselli (1999), Lloyd-Ellis (1999), and Galor and Moav (2000)).

The increase in wage inequality between the 1970s and 1990s is attributed to the increase in returns to unobserved individual abilities. This assumption implies that the increase in inequality should manifest itself in the increase in the dispersion of the persistent component of wages, a prediction at odds with the data on the increase in the transitory variance of wages. While the analysis in those articles is only qualitative, making it difficult to evaluate the quantitative importance of the increased returns to ability, the effects they describe are likely complementary to our theory. The fact that occupational mobility is observable and measurable reduces the degrees of freedom we have in accounting for the data.

The mechanism most closely related to our theory is proposed in Violante (2002). In his model, workers are randomly matched with machines that embody technologies of different vintages. Skills are vintage-specific, and the amount of skills that can be transferred to a newer machine depends on the technological distance between the vintages. He studies the effect of an increase in the productivity gap between vintages on wage inequality. Since workers receive wages proportional to the productivity of their machine, this increase in the productivity distance between machines leads to an increase in wage inequality. Wage dispersion is further increased because of the decline in skill transferability. Quantitatively, Violante's model accounts for about 30% of the rise in within-group inequality.

The paper is organized as follows. In Section 2, we document the facts motivating our analysis. We present the general equilibrium model with specific human capital and define equilibrium in Sections 3 and 4. The calibration and the quantitative experiment we perform are detailed in Section 5. The results are described in Sections 6 and 7. In Section 8, we discuss the results and some of our modeling choices. Section 9 concludes.

2 Facts

2.1 Changes in the Labor Market

From the early 1970s until the mid-1990s, the labor market underwent significant changes along several dimensions - wage inequality increased, wages became more volatile, and individuals switched occupations more often. Here we document these developments.

For most of the analysis, we use data from the Panel Study of Income Dynamics (PSID), which contains annual labor market information for a panel of individuals representative of the population of the United States in each year. We choose the PSID data for two major reasons. First, it is a panel data set - a feature that we exploit in our analysis. Second, the PSID is a unique data set that permits the construction of consistent measures of occupational mobility over the 1969-1997 period and one that allows us to deal with the problem of measurement error in occupational affiliation coding that plagues the analysis of mobility in any other U.S. data set.[1] We restrict the sample to male heads of household, aged 23-61, who are not self- or dual-employed, and who are not working for the government. The resulting sample consists of 76,381 observations over the 1969-1997 period, with an average of 2,633 observations a year. Additional sample restrictions are imposed in some of the analysis and are discussed when relevant.

The Concept of Wages.

We define wages of individual i in year t, w_{it}, as *real hourly earnings* which in the PSID are derived by dividing real annual earnings by total hours worked in a given year. We refer to this measure of wages as *Overall*. We also document the level and the change in two additional measures of wages that better correspond to the notion of wages in the model

[1] To deal with the measurement error problem, we develop a method based on the Retrospective Occupation-Industry Supplemental Data Files released by the PSID in 1999. This method allows us to obtain the most reliable estimates of the levels and trends in occupational mobility in the literature. We discuss this in detail in Kambourov and Manovskii (2002, 2004a,b).

developed below.

1. First, age and education have some effects on wages that are not present in the model. Conequently, we proceed to define wages net of the effect of these two variables. Following the standard approach in the literature, we obtain such a measure of residual wages through the following regression:

$$\ln w_{it} = \beta X_{it} + \epsilon_{it}, \tag{1}$$

   where X_{it} includes a constant term, a set of eight education dummies, a quartic in experience, and interactions of the experience quartic with three broad education categories.[2] Since returns to age and education are known to have changed over the period, we follow the standard practice and estimate this regression cross-sectionally for each year in the sample. Then, using the estimates $\hat{\beta}$ from the regression above, we define our first measure of residual (log) wages:

$$\ln w_{it}^{r} = \ln w_{it} - \hat{\beta} X_{it}.$$

   We refer to this measure of wages as *Within-Group 1*.

2. The *Within-Group 1* measure of wages, however, still does not provide a perfect match to the notion of wages in the model. It is too restrictive. First, occupational experience rises with age, on average. Second, the quality of occupational matches increases with age due to the search process. These are essential features of our model and their contribution should not be factored out from wages in the data. Thus, we include occupational tenure and occupational dummies into the regression and

[2]Following Katz and Autor (1999), the 8 education categories corresponding to years of schooling are: 0, 1-4, 5-8, 9, 10, 11, some college, college graduate and post-college. The experience quartic is interacted with dummies for less than high school, some college, and college or greater education. High school graduates are the omitted group.

subtract from wages the contribution of age that is not driven by (i) the accumulation of occupational human capital, or (ii) the increased quality of occupational matches over the life-cycle. In particular, first we regress:

$$\ln w_{it} = \beta X_{it} + \gamma Z_{it} + \epsilon_{it}, \tag{2}$$

where X_{it} contains the same variables as in (1) while Z_{it} contains a set of dummy variables for 3-digit occupations and the tenure of individual i in his three-digit occupation.[3] Then, using the estimates $\hat{\beta}$ from the regression above, we define our second measure of residual (log) wages as:

$$\ln \widetilde{w}_{it}^{r} = \ln w_{it} - \hat{\beta} X_{it}.$$

We refer to this measure of wages as *Within-Group 2*. This is the measure of wages which corresponds most closely to the measure of wages in our model.

In what follows, we document all three measures of wages in the data since two data limitations make our preferred *Within-Group 2* measure of wages not as precise as desired. First, occupational tenure is not well measured in the early years of the sample. The PSID asks individuals about their current occupation but does not ask them about the number of years they have worked in their current occupation. Therefore, one needs to follow individuals histories to construct occupational tenure. Since the PSID sample starts with a cross-section in 1968, before each of these individuals switches occupations for the first time in the sample we cannot be sure about their occupational tenure.[4] Thus, at least until the mid-1970s the occupational tenure measures are imprecise.

[3]We drop each year all observations which belong to a 3-digit occupation that has less than 7 observations in that year. The results are not sensitive to this cut-off.

[4]In an attempt to address this deficiency in the data we initialize occupational tenure in 1968 by employer tenure or, if that is not available, by position tenure.

Second, the three-digit occupational dummies are noisy, especially in the 1981-1996 period. Prior to 1981 occupational affiliation data comes from the Retrospective Occupation-Industry Supplemental Data Files. These files allow us to precisely identify occupational *switches*. It is not clear, however, how well these files identify occupational *names*. For example, if wee see an individual classified as a truck driver for three years and then his occupational code switches to that of a cook, we know with high degree of certainty that the individual switched his occupations. We are much less sure that the individual indeed was a truck driver before the switch. After 1981 the problem becomes even worse because only the noisy originally coded occupational affiliation data is available. In Kambourov and Manovskii (2002, 2004b), we study various procedures for identifying genuine occupational switches in the originally coded data. While we find that it is possible to identify *switches* quite precisely, there is much uncertainty as to the precise *names* of the occupations in which individuals are working.

Finally, the demographic structure of the population has been changing over time while it is not changing in the model. Thus, we construct weights for each individual in each year such that the weighed age-education-race population structure remains constant over time at its average level. When computing various statistics from the data, such as wage inequality, we weigh each observation using these weights. The results are very similar whether we use the changing actual or the fixed average population structure and, while in the paper we focus on the average population structure, we also report the corresponding facts for the actual population structure in Appendix I.

2.1.1 Increase in Wage Inequality

Table 1 and Figures 1, 2, and 3 show that wage inequality has increased substantially over the 1969-1996 period.[5] Overall inequality, as measured by the variance of log wages, increased from its average value of 0.225 in 1970-73 to 0.354 in 1993-96. Our measures of within-group inequality are consistent with the findings in the empirical literature on wage inequality (see Katz and Autor (1999)) and reveal that a substantial fraction of the increase in overall inequality was accompanied by an increase in within-group inequality. As expected, our *Overall* measure of wages delivers the highest level of inequality, followed by our *Within-Group 2* measure. The *Within-Group 1* measure exhibits the lowest level of inequality. The results for the other measures of wage dispersion, such as the Gini coefficient or log 90/10 ratio, are similar.

In Figure 4 we plot the percentage change in wages by percentiles of the wage distribution. The figure reveals that the increase in wage inequality reflects changes that affected all parts of the wage distribution. In particular, between 1970 and 1993 real hourly earnings have declined for most American men and have increased only for those in the top percentiles. These findings are similar to those reported in Gottschalk (1997) and Topel (1997).[6]

[5] For comparability with the results in the literature the sample is further restricted by dropping in each year (i) all observations with a nominal hourly wage which is lower than half the minimum wage in that year, and (ii) all observations which report less than 520 hours worked in that year.

[6] While we have data only on individual wages, a more relevant concept for our analysis might be that of total compensation. Using the establishment survey data for the 1981-1997 period, Pierce (2001) finds that a changing distribution of nonwage compensation reinforces the finding of rising wage inequality. Nonwage compensation is strongly positively correlated with wages, and inequality of total compensation rose more than did wage inequality. If one incorporates workplace amenities, such as daytime versus evening/night work and injury rates, into the definition of compensation, Hamermesh (1999) suggests that the change in earnings inequality between the early 1970s and early 1990s has understated the change in inequality in returns to work measured according to this definition.

2.1.2 Decline in Wage Stability

Gottschalk and Moffitt (1994) found that, during the 1980s, the short-term earnings volatility increased sharply compared to the 1970s. Formally, let y_{it} denote the log annual earnings of individual i in year $t = 1, 2, ..., T$. One can decompose y_{it} into a permanent and a transitory component in the following way:

$$y_{it} = \pi_i + \eta_{it},$$

where π_i is the mean log wage of individual i over T years, while η_{it} is the deviation of y_{it} from the individual mean log wage in year t. Denote by $var(\eta_i)$ the variance of η_{it} for individual i over the T years. Consider two nine-year periods – 1970-78 and 1988-96. Table 2 shows that on all three measures of wages the average (across individuals) variance of η_{it} increased substantially between the first an the second periods. These results imply that workers faced considerably higher wage variability in the 1990s than in the 1970s.[7]

2.1.3 Increase in Occupational Mobility

As summarized in Table 3 and Figure 5, we find that occupational mobility in the U.S. has increased from 16% in the early 1970s to 21% in the early 1990s, at the three-digit level (see Appendices IV - VI for the description of the occupational codes). Occupational mobility is defined as the fraction of currently employed individuals who report a current occupation different from their most recent previous report.[8] The three-digit classification

[7]The result that short-term income volatility has increased significantly over the period is robust to various alternative assumptions in modeling the covariance structure of the earnings process in, e.g., Moffitt and Gottschalk (1995) and Heathcote, Storesletten, and Violante (2004). Blundell and Preston (1998) find a strong increase in the variance of transitory income shocks between 1968 and 1992 in British data. They use consumption data to identify transitory and permanent components of income shocks.

[8]For example, an individual employed in two consecutive years would be considered as switching occupations if she reports a current occupation different from the one she reported in the previous year. If an individual is employed in the current year, but was unemployed in the previous year, a switch will be recorded if current occupation is different from the one he reported when he was most recently employed.

defines more than 400 occupations: architect, carpenter, and mining engineer are a few examples. Figure 6 also shows that even at the one-digit level - a classification that consists of only nine broad occupational groups - there was a substantial increase in occupational mobility. Rosenfeld (1979) suggests that occupational mobility did not exhibit any trend in the 1960s.[9]

Several additional results from Kambourov and Manovskii (2004b) are relevant to this study. First, occupational mobility has increased for most age-education subgroups of the population: it increased for those with a high-school diploma as well as for those with a college degree and for workers of different ages. Second, mobility has increased in all parts of the occupational tenure distribution. Third, the increase in occupational mobility was not driven by an increased flow of workers into or out of a particular one-digit occupation. Thus, we find no evidence of an increase in stepping-stone mobility described in Jovanovic and Nyarko (1997). Finally, we note that occupational switches are fairly permanent: only around 20% of switchers return to their three-digit occupation within a four-year period.

2.2 Occupational Specificity of Human Capital

In Kambourov and Manovskii (2002) we found substantial returns to tenure in a three-digit occupation - an increase in wages of at least 12% after 5 years of occupational experience. Table 4 summarizes the finding and the estimation procedure. Furthermore, we found that when experience in an occupation is taken into account, tenure within an industry or with an employer has little effect on workers' wages. In other words, as long as a worker remains in the same occupation, her wages will keep growing regardless of whether she

[9]Parrado and Wolff (1999) and Parrado, Caner, and Wolff (2005) also argue in favour of an increase in occupational mobility in the United States from the late 1960s till the early 1990s. Moscarini and Vella (2003), using the March CPS, and Moscarini and Thomsson (2006), using the matched monthly CPS, find a similar increase in occupational mobility on a sample similar to ours and for the overlapping 1976-1997 period.

switches her industry or her employer. This finding is consistent with human capital being occupation-specific.

Numerous other authors using different methodologies and data from different countries have also found evidence of the occupational specificity of human capital and of the importance of the occupational search process. In earlier papers, Shaw (1984, 1987) argued that investment in occupation-specific skills is an important determinant of earnings. McCall (1990) emphasized the importance of occupational matching. More recently, Kwon and Meyersson Milgrom (2004), using Swedish data, found that firms prefer to hire workers with relevant occupational experience, even when this involves hiring from outside of the firm. In addition they find no returns to firm tenure once tenure in an occupation is accounted for. Zangelidis (2004), using a methodology similar to ours, finds large returns to occupational tenure in British data. Pavan (2005) estimates a structural model using NLSY data and finds substantial returns to occupational tenure (the results are not readily comparable, however, because he uses a different definition of occupation). Hagedorn, Kambourov, and Manovskii (2005) find substantial returns to occupational tenure in a large administrative German data set from the Institute for Employment Research (IAB). Kambourov, Manovskii, and Plesca (2005), using data from the Canadian Adult Education and Training Survey, find substantial losses in human capital when workers switch occupations. The results in these papers point to the same conclusion: returns to occupational tenure are large. Consequently, understanding the effects of occupational mobility on wage inequality appears important. We explore this relationship below.

3 An Equilibrium Model with Occupation-Specific Experience

Environment. The economy consists of a continuum of occupations of measure one and ex-ante identical individuals of measure one. Individuals die (leave the labor force) each period with probability δ and are replaced by newly born ones. There are two experience levels in each occupation: workers are either inexperienced or experienced. Experience is occupation-specific, and newcomers to an occupation, regardless of the experience they had in their previous occupations, begin as inexperienced workers. Each period, an inexperienced worker in an occupation becomes experienced with probability p. Those who, at the beginning of the period, decide to leave their occupation, search for one period and arrive in a new occupation at the beginning of the next period.[10] Search is random in the sense that the probability of arriving to a specific occupation is the same across all occupations.

Preferences. Individuals are risk-neutral and maximize:

$$E\sum_{t=0}^{\infty}\beta^t(1-\delta)^t c_t, \tag{3}$$

where β is the time-discount factor and c_t denotes consumption in period t. The decision rules and equilibrium allocations in the model with risk-neutral workers are equivalent to those in a model with risk-averse individuals and complete insurance markets.

Production. All occupations produce the same homogeneous good. Output y in an

[10] The assumption that a worker switching occupations searches for one period is made in order to make the experiment we conduct in this paper more interesting and should not be interpreted as modeling unemployment. An alternative assumption would be to change the timing of the model so that the separation decisions are taken at the end of a period so that a switching worker instantaneously starts the new period in a new occupation. This would imply that we force individuals to work for one period in an occupation they may not like. Thus an increase in the variance of idiosyncratic occupation productivity shocks will necessarily increase wage inequality. We choose to allow workers to escape the low realizations of occupation productivity shocks in order to make the relationship between occupational mobility and wage inequality truly endogenous.

occupation is produced with the production technology

$$y = z\left[a g_1^{\rho} + (1-a) g_2^{\rho}\right]^{\frac{\gamma}{\rho}}, \tag{4}$$

where $\rho \leq 1,\ 0 < \gamma < 1,\ 0 < a < 1,\ g_1$ is the measure of inexperienced individuals working in the occupation, g_2 is the measure of experienced individuals working in the occupation, and z denotes the idiosyncratic productivity shock. The productivity shocks evolve according to the process

$$\ln(z') = \alpha + \phi \ln(z) + \epsilon', \tag{5}$$

where $0 < \phi < 1$ and $\epsilon' \sim N(0, \sigma_\epsilon^2)$. We denote the transition function for z as $Q(z, dz')$.

There are a large number of competitive employers in each occupation, and the wages that the inexperienced and experienced workers receive in an occupation are equal to their respective marginal products. We assume that there are competitive spot markets for the fixed factor in each occupation, implied by the production function. Households own the same market portfolio of all the fixed factors in the economy which yields the same return. Since we study only the inequality of *wages* in this paper, without loss of generality, we do not explicitly model households' asset income.

Occupation Population Dynamics. Let $\psi = (\psi_1, \psi_2)$ denote the beginning of the period distribution of workers present in an occupation, where ψ_1 is the measure of inexperienced workers while ψ_2 is the measure of experienced ones. At the beginning of the period, the idiosyncratic productivity shock z is realized. Some individuals in an occupation (ψ, z) could decide to leave the occupation and search for a better one. Denote by $g(\psi, z) = (g_1, g_2)$, the end of the period distribution of workers in an occupation, where g_j is the measure of workers with experience $j = 1, 2$ who decide to stay and work in an occupation

(ψ, z).[11]

Let S be the economy-wide measure of workers searching for a new occupation. Then, S and $g(\psi, z)$ determine the next period's starting distribution, ψ', of workers over experience levels in each occupation. The law of motion for ψ in an occupation is

$$\psi' = (\psi'_1, \psi'_2) = \Gamma(g(\psi, z)) = (\delta + (1-\delta)S + (1-p)(1-\delta)g_1, p(1-\delta)g_1 + (1-\delta)g_2). \quad (6)$$

In the beginning of the next period, the number of inexperienced workers who will start in an occupation is equal to (i) the employed inexperienced workers this period who survive and do not advance to the next experience level, plus (ii) the newly arrived workers - those who are searching this period and survive, $(1-\delta)S$, and the new entrants into the labor market, δ.[12] Similarly, the measure of experienced workers in the beginning of the next period is equal to the employed experienced workers this period who survive, plus those employed inexperienced this period who survive and become experienced next period.

Individual Value Functions. Consider the decision problem of an individual in an occupation (ψ, z) who takes as given $g(\psi, z)$, S, and V^s - the value of leaving an occupation and searching for a new one. Denote by $w_1(\psi, z)$ the wage of the inexperienced workers in occupation (ψ, z). Then, $V_1(\psi, z)$, the value of starting the period in an occupation (ψ, z) as an inexperienced worker, is

$$V_1(\psi, z) = \max\left\{V^s, w_1(\psi, z) + \beta(1-\delta)\int \left[(1-p)V_1(\psi', z') + pV_2(\psi', z')\right] Q(z, dz')\right\}. \quad (7)$$

If the worker leaves the occupation, her expected value is equal to V^s. The value of staying

[11] In general, individual decisions depend on the aggregate state of the economy as well. Since we restrict our analysis to steady states, the aggregate variables in the economy are constant. Thus, we omit them to keep the notation concise.

[12] Since workers in the model have a choice of whether to stay in their occupation or leave, we find it reasonable to model new entrants this way - they start by observing the current economic conditions in a specific occupation and decide then whether to keep looking for another one or not. Forcing the new comers to enter as unemployed does not affect our results.

and working in the occupation is equal to the wage received this period plus the expected discounted value from the next period on, taking into account the fact that with probability p she will become experienced next period and with probability δ she will die.

Similarly, $V_2(\psi, z)$, the value of an experienced worker in an occupation (ψ, z), is

$$V_2(\psi, z) = \max\left\{V^s, w_2(\psi, z) + \beta(1-\delta)\int V_2(\psi', z')Q(z, dz')\right\}. \tag{8}$$

As in the case of inexperienced workers, if an experienced worker leaves the occupation, her expected value is equal to V^s. The value of staying and working in the occupation is equal to the wage received this period plus the expected discounted value from the next period on.

Stationary Distribution. We are focusing on a stationary environment characterized by a stationary, occupation-invariant distribution $\mu(\psi, z)$:

$$\mu(\Psi', Z') = \int_{\{(\psi,z):\psi'\in\Psi'\}} Q(z, Z')\mu(d\psi, dz), \tag{9}$$

where Ψ' and Z' are sets of experience distributions and idiosyncratic shocks, respectively.

4 Equilibrium

Definition. A stationary equilibrium consists of value functions $V_1(\psi, z)$ and $V_2(\psi, z)$, occupation employment rules $g_1(\psi, z)$ and $g_2(\psi, z)$, an occupation-invariant measure $\mu(\psi, z)$, the value of search V^s, and the measure S of workers switching occupations, such that:

1. $V_1(\psi, z)$ and $V_2(\psi, z)$ satisfy the Bellman equations, given V^s, $g(\psi, z)$, and S.

2. Wages in an occupation are competitively determined:

$$\begin{aligned} w_1 &= z\gamma a g_1^{\rho-1}\left[a g_1^\rho + (1-a)g_2^\rho\right]^{\frac{\gamma-\rho}{\rho}}, \\ w_2 &= z\gamma(1-a) g_2^{\rho-1}\left[a g_1^\rho + (1-a)g_2^\rho\right]^{\frac{\gamma-\rho}{\rho}}. \end{aligned}$$

3. The occupation employment rule $g(\psi, z)$ is consistent with individual decisions:

   (a) If $g_1(\psi, z) = \psi_1$ and $g_2(\psi, z) = \psi_2$, then $V_1(\psi, z) \geq V^s$ and $V_2(\psi, z) \geq V^s$.

   (b) If $g_1(\psi, z) < \psi_1$ and $g_2(\psi, z) = \psi_2$, then $V_1(\psi, z) = V^s$ and $V_2(\psi, z) \geq V^s$.

   (c) If $g_1(\psi, z) = \psi_1$ and $g_2(\psi, z) < \psi_2$, then $V_1(\psi, z) \geq V^s$ and $V_2(\psi, z) = V^s$.

   (d) If $g_1(\psi, z) < \psi_1$ and $g_2(\psi, z) < \psi_2$, then $V_1(\psi, z) = V^s$ and $V_2(\psi, z) = V^s$.

4. Individual decisions are compatible with the invariant distribution:

$$\mu(\Psi', Z') = \int_{\{(\psi,z):\psi' \in \Psi'\}} Q(z, Z')\mu(d\psi, dz).$$

5. For an occupation (ψ, z), the feasibility conditions are satisfied:

$$0 \leq g_j(\psi, z) \leq \psi_j \qquad \text{for } j = 1, 2.$$

6. Aggregate feasibility is satisfied:

$$S = 1 - \int [g_1(\psi, z) + g_2(\psi, z)]\, \mu(d\psi, dz).$$

7. The value of search, V^s, is generated by $V_1(\psi, z)$ and $\mu(\psi, z)$:

$$V^s = (1 - \delta)\beta \int V_1(\psi, z)\mu(d\psi, dz).$$

The algorithm for computing equilibrium in this model is presented in Appendix III.

5 Quantitative Analysis

5.1 The Experiment

The model parameters to be calibrated are:

1. δ - the probability of an individual dying,

2. β - the time discount rate,

3. p - the probability of an inexperienced individual becoming experienced,

4. γ - the curvature parameter of the production function,

5. a - the distribution parameter of the production function,

6. ρ - the substitution parameter of the production function,

7. α - the unconditional mean of the stochastic process generating shocks z,

8. ϕ - the persistence parameter of the stochastic process generating shocks z,

9. σ_ϵ^2 - the variance of the innovations in the stochastic process generating shocks z.

The main experiment we perform in this paper is as follows. The first six parameters above are assumed to be invariant over the 1968-97 period. The last three parameters, α, ϕ, and σ_ϵ, which govern the idiosyncratic occupational productivity shocks, are assumed to be different in the early 1970s and mid-1990s. Thus, we calibrate α, ϕ, and σ_ϵ to match the properties of occupational mobility separately in the 1970-73 and 1993-96 periods. At no point in the calibration do we target wage inequality.

5.2 Calibration Details

Most of the model parameters are directly imputed from the data. Other parameters are chosen to match observed moments, e.g., occupational mobility. We use the PSID data and maintain the sample restrictions described in the beginning of Section 2.

We choose the model period to be two months. Since the PSID has annual frequency, we observe only an annual rate of occupational mobility in the data. To maintain consistency between the model and the data we will pretend that we observe each individual in the model only every sixth period. We choose $\delta = 0.0042$ to generate an expected working lifetime of 40 years. We set $\beta = 1/(1+r)$, where r represents an annual interest rate of 4%.

An investigation of the estimated returns to occupational tenure suggests that the rate of growth of wages slows down considerably once an individual reaches approximately 10 years of occupational experience. Thus, we choose $p = 0.0167$, which implies that it takes, on average, 10 years for a newcomer to an occupation to become experienced in that occupation. We investigate the sensitivity of the results with respect to p in Sections 6 and 7.

Production Function. We select $\gamma = 0.68$ to match the labor share implicit in the NIPA accounts. To obtain a and ρ, we employ the following procedure. Taking the ratio of the wages paid to the experienced and inexperienced workers in an occupation, one obtains:

$$\left(\frac{w_2}{w_1}\right) = \frac{1-a}{a}\left(\frac{g_2}{g_1}\right)^{\rho-1}. \tag{10}$$

The parameters a and ρ can then be estimated, using the following regression model:

$$\ln\left(\frac{w_2}{w_1}\right)_{it} = \xi_0 + \xi_1 \ln\left(\frac{g_2}{g_1}\right)_{it} + \nu_{it}, \tag{11}$$

where i indexes occupations, t indexes time, and ν_{it} is a classical measurement error. The parameters of interest are obtained from the following relations: $a = 1/(e^{\hat{\xi_0}} + 1)$ and $\rho = \hat{\xi_1} + 1$. The estimation procedure is summarized in Appendix II. The results imply that $a = 0.44$ and $\rho = 0.73$. We investigate the sensitivity of the results with respect to these parameters in Sections 6 and 7.

Stochastic Process. We determine the shock values z_i and the transition matrix $Q(z, \cdot)$ for a 15-state Markov chain $\{z_1, z_2, ..., z_{15}\}$ intended to approximate the postulated continuous-valued autoregression. We restrict z_1 and z_{15} as implied by three unconditional standard deviations of $\ln(z)$ above and below the unconditional mean of the process, respectively.

We first choose ϕ and σ_ϵ to match the following observations for the 1970-73 period:

1. The average annual rate of occupational mobility at the three-digit level using the average population structure (summarized in Table 3).

2. The average number of switches for those who switched a three-digit occupation at least once over the period. This statistic is equal to 1.54 over the 1970-73 period and 1.71 over the 1993-96 period.[13]

Next, we choose ϕ and σ_ϵ to match the corresponding observations for the 1993-96 period. We normalize α to be equal to zero in the first period and adjust it in the second period to keep real average wages constant.[14]

Table 5 summarizes the values of the parameters assumed to be fixed in both periods. Table 6 contains the values of α, ϕ, and σ_ϵ with which the model exactly matches calibration targets in both periods (see Table 7). The values of the shocks and the stationary distributions of occupations over shocks in both periods can be found in Table 8.

[13]This statistic distinguishes if most of the occupational mobility is accounted for by a subset of workers switching occupations repeatedly or by different workers switching occasionally. Subject to the environment, it is also a measure of how directed a search is, i.e., how long, on average, it takes a worker switching occupations to find a new one that she likes. To compute the average number of occupational switches in the 1970-73 period, we restrict the sample to those who satisfy our usual sample restrictions described in Section 2 and have an occupational code in every year of the 1969-73 interval. This implies that sample size is constant in every year. The procedure used to compute this statistic in the 1993-96 period is similar.

[14]The choice of values of α in either period has no effect on the values of the statistics we are interested in in this paper. There is some controversy in the literature whether average real wages of male workers have changed in the data between the early 1970s and mid-1990s. Depending on the choice of the deflator and of the exact years over which the comparison is made, some papers find them declining slightly while some others find them slightly increasing. Since this choice has no importance for our results, we pick the middle point in the range of the available estimates.

6 The Level of Wage Inequality and Wage Stability

We did not target the dispersion or volatility of wages when calibrating the model. Instead, we targeted occupational mobility and let the model determine wages endogenously. Thus, the first question we ask is whether the calibrated model with occupation-specific human capital generates reasonable levels of wage inequality and wage volatility. In the next section we will ask whether the increase in occupational mobility over time can help us understand the rise in the dispersion and in the volatility of wages.

6.1 Results

Table 9 reports the level of wage inequality and wage stability in the model and in the data for the 1970-1973 period.[15] The results indicate that the model, calibrated to match the facts on occupational mobility in that period, generates wage inequality and wage instability similar to those in the data. For example, the variance of log wages in the model is over 70% of its within-group counterpart in the data, while the log 90/10 ratio and the gini coefficient in the model are around 90% of their respective within-group measures in the data.

To investigate the sensitivity of these findings to the choice of the parameter values, we first conduct a "comparative statics" analysis - we change one by one the values of a, ρ, p, and γ, and, without recalibrating the model, investigate the effects such a change has on the results. The results of these experiments, summarized in Table 11, indicate that occupational mobility and wage inequality change slowly, smoothly and monotonically as we vary a, ρ, p, and γ.

Next, we investigate the sensitivity of the results with respect to p ranging from 0.0208

[15]Even though the discussion in this section focuses on the 1970-1973 period, we would get the same message if we were to analyze instead the 1993-1996 period.

to 0.0139, implying that it takes either 8 or 12 years to become skilled in an occupation. Given the choice of p, we re-estimate the parameters of the production function a and ρ, and then recalibrate all the remaining parameters of the model to match the same targets as in the benchmark calibration. Despite substantial changes in the implied parameter values, both recalibrated models generate substantial levels of wage inequality.

6.2 The Importance of Human Capital

What accounts for the model's ability to generate substantial levels of wage dispersion? As we discuss in this section, occupation-specific human capital is of central importance. To isolate its effect we now repeat all the analysis in an environment without occupation-specific human capital (the model remains exactly the same with the only change that people of various occupational experience levels are perfectly substitutable in occupational production and are equally productive).

The results are summarized in Table 10. In the first experiment we look at the effect of eliminating occupation-specific human capital if we keep the values of all the parameters at their values in the benchmark calibration of the model with human capital. We find that without human capital occupational mobility increases substantially while the variance of log wages declines from 0.120 to 0.069. In the second experiment we calibrate the model without human capital to match the same targets as in the benchmark calibration. We find that in the re-calibrated model the variance of log wages drops to 0.03. This result echoes the findings in Hornstein, Krusell, and Violante (2006) that reasonably calibrated standard search and matching models of equilibrium unemployment generate only small amount of frictional wage dispersion. Thus, it turns out that, without the loss of the specific human capital, the costs of switching occupations in terms of forgone earnings are too small to support a substantial wage dispersion. This is despite the fact that we do not model unemployment insurance, home production and the value of leisure (although we assume that individuals are risk-neutral – an assumption that decreases the cost of switching occupations in the model).

To see this differently, recall that the model period in our benchmark calibration is two months. With this periodicity the model generates quite reasonable durations of unemployment – 9.4 weeks in the first period and 10.3 weeks in the second period.[16] When we re-calibrate the model with human capital with a model period of three (or one) months we find that the variance of the log wages goes up (or down) by about 20%. While this change is sizable, it is small relative to the effect of eliminating specific human capital.

Why does the presence of occupation-specific human capital play such a crucial role in generating substantial wage inequality? There are several channels that account for this finding.

First, the presence of occupation-specific human capital leads to the dispersion of human capital levels and wages within occupations. Since computing the model is fairly hard we allowed for only two levels of occupational human capital. This limits the wage dispersion within occupations in the model. But it is there, nevertheless.

Second, and perhaps most importantly, the presence of human capital generates a lock-in-effect. Experienced workers who have accumulated a significant amount of specific human capital are willing to ride the shocks together with their occupations rather than switch them and destroy specific human capital. Less experienced workers are also less willing to switch occupations in the model not to forgo the accumulation of human capital in their occupation.

Third, workers equalize expected present values of the their earnings rather than current

[16]The level of unemployment in the model is also within a reasonable range - 4.01% in the first period and 6.01% in the second period.

wages - workers are indifferent between a flat earnings profile and an increasing earnings profile as long as the present discounted values are the same. In the model some workers are willing temporarily to work at lower wages in their occupation because of the possibility of becoming experienced and earn substantially higher wages.[17]

7 The Increase in Wage Inequality and the Decline in Wage Stability

We now turn to analyzing the model's ability to account for the increase in wage inequality and the decline in wage stability in the 1969-1997 period. As mentioned earlier, the nature of the experiment is to recalibrate the process of the shocks to occupations in order to match the facts on occupational mobility without targeting in any way wage inequality.

7.1 Results

The results, summarized in Table 12, show the change in wage inequality and wage stability as we move from the early 1970s to the mid-1990s. The main message from the results is that the model is quite successful in accounting for the changes in the wage structure over the period as it captures almost all of the observed increase in within-group wage inequality and decline in wage stability. Further, in order to look deeper at the increase in wage inequality, we use the calibrated model to construct a graph of the relative change

[17]The relative wages of experienced and inexperienced workers in an occupation depend on the number of workers of each type. When an occupation experiences a good productivity shock, a larger fraction of the inexperienced workers who come to that occupation will decide to stay and work in that occupation. This decreases the wages of experienced workers but by less than the wages of inexperienced workers (since $\gamma < \rho$). Thus, some inexperienced workers may be induced to work in a highly productive occupation, despite receiving relatively low wages, in expectation of gaining experience and receiving higher wages in the future.

Note as well that the fact that the estimates of the production function parameters entail $\rho < 1$ implies that it is possible for experienced workers in an occupation to receive lower wages than the inexperienced ones do. This indeed happens occasionally in the calibrated model. However, the fraction of the population that works in the occupations where this happens is very small - less than 1%. Eliminating such occupations from the analysis altogether leaves all of our results virtually unchanged.

in wages by percentiles - Figure 7 graphs the percentage change in real hourly earnings by percentiles both in the model and in the data.[18] The figure illustrates that the model does an excellent job matching the observation that the increase in residual wage inequality in the data reflected changes that affected all parts of the wage distribution. In particular, as in the data, the model predicts a decline of wages for most individuals and an increase only for those at the top percentiles.

Inspecting the results in Table 13 from the re-calibrations of the model with different choices of p, one finds that, despite substantial changes in the implied parameter values, both recalibrated models generate increases in wage inequality that are similar to those in the data. Similar to the benchmark calibration, in all cases it is necessary to increase the variance of the innovations in the productivity shock process and to decrease its persistence to match the increase in occupational mobility between the early 1970s and mid-1990s.

What accounts for the ability of the model to generate a substantial increase in wage dispersion in response to the changes in occupational mobility? In order to understand the ability of the model to account for the increase in wage inequality, it is instructive to analyze the distributions of employed workers across productivity shocks in the calibrated model in both periods. It turns out that the distribution of workers over productivity shocks in the mid-1990s is quite similar to the corresponding distribution in the early 1970s despite the fact that the dispersion of the shocks is higher in the latter period. This implies that more workers choose to remain in the relatively unproductive occupations. Why would they do so? In the mid-1990s, shocks are more dispersed and are less persistent. An inexperienced worker who finds himself in a relatively unproductive occupation this period

[18]The graph for the data represents the percentage change in real hourly earnings by percentiles using the *Within-Group 2* measure of wages and average population structure. Figures 4 and A-4 show the corresponding graphs for the other measures of wages and the actual population structure.

has an option of switching his occupation and searching one period for a new occupation or remaining in the current occupation and accumulating human capital. Since searching for a currently productive occupation is less attractive because of the decreased persistence of the high productivity shocks in the 1990s, more workers choose to remain on the relatively unproductive occupation. In addition, there is a higher chance of this occupation receiving a high productivity shock in the next period, and this provides additional incentives to preserve human capital. These two effects lead to an increase in the average size of the occupations in the middle of the distribution of productivity shocks (the shocks that have a high mass in the stationary distribution). When a low productivity shock hits one of these larger occupations, a bigger mass of workers leave it, driving the increase in occupational mobility.

7.2 Evaluating some Alternative Theories of the Increase in Occupational Mobility and Wage Inequality

In this Section we qualitatively study whether changes in occupational mobility and wage inequality could have been driven by the changes in the relative importance of occupation-specific human capital and changes in the non-human capital costs of switching occupations.

An increase in the relative productivity of experienced workers. The analysis of the model's performance with respect to a in Table 11 helps evaluate an alternative theory of the increase in wage inequality. It suggests that wage inequality might have increased because of an increase in the relative productivity of experienced workers. Suppose this is indeed what happened (say, a declined from 0.44 to 0.40) while the variability of occupational productivity shocks did not change over the period (it remained at its early 1970s level). Such a substantial (23 percent) increase in the relative productivity of experienced workers would indeed result in some increase in the variance of logs (from 0.120 to 0.149) and an increase in the variance of transitory log wages (from 0.096 to 0.110). The theory, however, would have the strongly counterfactual prediction of a decline in occupational mobility from 0.159 to 0.102. These results are similar in spirit to those in Den Haan, Haefke, and Ramey (2001) and are intuitive. If the returns to occupational experience increase, individuals respond by accumulating more human capital and switching their occupations less often.

Decline in the importance of the occupation-specific human capital. Alternatively, one may ask what would have happened to occupational mobility and wage inequality if human capital generated by occupation-specific experience became less important over time. We evaluate this theory in Table 11 by increasing a from 0.44 to 0.48, implying a substantial (19 percent) decline in the relative productivity of experienced workers. As one might expect, the decline in importance of occupation-specific human capital in the model will result in an increase in occupational mobility (from 0.159 to 0.211). It would, however, imply a decline in wage inequality (the variance of logs will decrease from 0.120 to 0.101) and the variance of transitory log wages (from 0.096 to 0.086) that is clearly in conflict with the data.

Could Declining Search Costs Have Caused the Increase in Occupational Mobility and Wage Inequality? Finally, suppose that the only change in the economic environment between the early 1970s and the mid-1990s was the decline in the cost of search that was not related to the destruction of human capital. Is this consistent with the stylized facts motivating this paper? Formally, we perform the following experiment. The model is calibrated to match the targets in the early 1970s. Then we decrease the model period from two months to one month. We recompute all the time-invariant parameters of the model to be consistent with the new model period. Since the model period is now twice shorter, we rescale the persistence of the productivity shocks $\phi^{new} = \sqrt{\phi^{old}}$ and the standard deviation of its innovations, $\sigma_\epsilon^{new} = \sigma_\epsilon^{old}/\sqrt{1+(\phi^{new})^2}$. The rationale for this rescaling is that we want to keep the environment constant in the following sense: conditional on a realization of the shock in period t, we keep the expected value and the expected variance of the shock in period $t+2$ identical to what they would have been in period $t+1$ with a twice longer model period.[19]

The results of this experiment are presented in Table 14. They indicate that a substantial decline in search costs is compatible with the data on occupational mobility. The predictions about wage inequality, however, are strongly counterfactual: both the dispersion and the volatility of wages decline substantially. We conclude from this experiment that if the cost of switching occupations did decrease over the period, the observed increase in wage inequality is substantially lower than what it would have been otherwise. If this is true, economists have a considerably more difficult puzzle to tackle when trying to account for the increase in wage inequality.

8 Discussion

8.1 Results

Inequality Within and Across Occupations. In the calibrated model the increase in the variability of occupational productivity shocks results in a sizable increase in dispersion of wages across occupations with a smaller increase of wage dispersion within occupations.

[19]The relationship is not exact because when moving from the two to one month model period we maintain the AR(1) assumption on the evolution of shocks. Quantitatively, however, the effect of this inconsistency is negligible.

We now contrast this implication of the model with the data. In Table 15 we summarize the variance of log wages between and within three-digit occupations in the 1970-1973 and 1993-1996 periods.[20]

The results indicate that, using the *Overall* measure of wages, the inequality between occupations increases substantially from 0.099 to 0.192 while the inequality within occupations increases from 0.127 to 0.154. As we move to the *Within-Group 1* and the *Within-Group 2* measures of wages, mainly between-occupation inequality is affected suggesting that there is much greater heterogeneity by age and education across occupations than within occupations. The *Within-Group 2* measure of wages, which is the one closest to the notion of wages in our model, displays an increase in inequality between occupation from 0.067 to 0.141 and an increase in the inequality within occupations from 0.109 to 0.140.

Recall that *names* of occupations are noisy in the PSID, especially, in the 1981-1997 period. Misclassifying the occupational affiliation of workers tends to increase the level of within-occupation inequality and to decrease the level of between-occupation inequality. Due to higher noise in occupational names in the 1990s when only the originally coded data are available from the PSID, the computed increase in within-occupation inequality is most likely an upper bound on the actual increase in the data.

The level and increase in between-occupation inequality in the model is similar to that in the data. Our model has much less to say about within-occupation inequality. In the data, the level of within-occupation inequality appears significant and the increase is probably not negligible either. For computational reasons we have only two experience levels in an occupation as a result of which we cannot generate the levels of within-occupation inequality

[20]We define between-occupation wage inequality as the variance of the mean of log wages in an occupation while within-occupation inequality is defines as the average (across all occupations) variance of log wages within an occupation. The results on one and two-digit levels are similar.

observed in the data. In addition, we have abstracted from any ex ante heterogeneity.

Properties of the Shock Process. We found that in order to account for the change in occupational mobility the persistence of shocks to occupations must have declined and their variance increased. What are the possible economic reasons for this? Can we obtain some independent evidence of this happening in the data? We discuss these two questions in this Section.

Evaluating what caused the increase in variability of occupational shocks is well beyond the scope of this paper. Here, without presuming to be thorough and rigorous, we suggest a number of alternatives potentially accounting for the increase in the variance and a decline in persistence of occupational shocks. Distinguishing (quantitatively) between the importance of these and other mechanisms, we believe, provides a promising avenue for future research.

1. There is evidence suggesting that nowadays technologies arrive at a faster rate than 30 years ago (see Violante (2002)). One would expect that the arrival of a new technology would not affect uniformly all occupations. Instead it would benefit some at the expense of others resulting in a higher variance in the occupational shocks. It could also decrease the persistence of these shocks - a technology today might decrease the productivity of a given occupation relative to the other occupations while another new technology a few periods later can increase its relative productivity.[21]

2. Opening the economy to international trade makes occupations more vulnerable to shocks than before. First, opening the economy to trade implies that any productivity changes in particular sectors in foreign countries would have an impact on similar

[21] One may, for example, recall the booming demand for web page designers just a few years ago that all but disappeared when simple web page programming software became widely available.

sector in the domestic economy and would, as a result, affect a certain set of occupations. Second, any changes in foreign demand would also affect particular sectors (and sets of occupations) of the domestic economy. The variance of the occupational shocks would increase while it is possible for the persistence to decline since demand (or productivity) sectoral changes in the rest of the world might hurt a particular domestic occupation in the current period while increasing its relative importance a few periods later.

3. There are other potential suspects. Labor unions that span several occupations may insulate workers from transitory fluctuations in demands for the services of particular occupations. De-unionization exposes workers to those shocks. Similarly, each firm employs workers from different occupations. Risk-averse workers who do not have access to perfect insurance may want firms to smooth their transient occupational shocks. If capital markets become more efficient over time, the demand for such insurance declines, and workers again become more exposed to occupational shocks that are, from the workers' point of view, more dispersed and less persistent.

Thus, while it does not appear unreasonable that occupational shocks became more dispersed and less persistent, is there any evidence of this in the data? Consider the change in the persistence of average wages in occupations and the change in the variance of the innovations to them. In particular, we use the PSID and our usual sample restrictions to construct a panel of the log of average wages of 3-digit occupations. Next, we use 1969-1980 and 1985-1996 sub-periods to estimate two AR(1) processes loosely corresponding to the two steady states of the model. We find that the persistence of log average wages in an occupation declined from 0.27 in the 1970s to 0.19 in the 1990s. The standard deviation of the innovations to occupational average wages increased from 0.12 in the 1970s to 0.20

in the 1990s. We obtain similar results when using *Within-Group 1* and *Within-Group 2* measures of wages and coarser occupational classifications.

The increase in variance and a decline in persistence of the average occupational wages suggest an increase in variance and a decline in persistence of occupational productivities. Unfortunately due to the data limitations, we cannot directly estimate such shocks in the data. In order to measure the shocks to occupations as residuals from the wage equations (using our model) we need to know (i) one's tenure in his occupation each year, and (ii) the actual occupation that he is working in. First, as discussed above, occupational tenure is not well defined in the early years of the sample. The PSID asks individuals about their current occupation but does not ask how long they have worked in their current occupation. Therefore, one needs to construct occupational tenure by following individuals over time. This implies that until the mid to late 1970s the occupational tenure measures are imprecise. Second, the three-digit occupational dummies are noisy, more so in the 1981-1996 period. Thus it appears impossible to infer from the data the *changes* in the shock process with any degree of certainty.[22] Instead, we use the model and our calibration strategy in order to infer how the shock structure must have changed in order to match the change in occupational mobility, which we *can* measure precisely.

8.2 Modeling Choices

Productivity vs. Demand Fluctuations. We have modeled occupations as producing homogeneous good and occupational shocks as shocks to the production function in an occupation. There is an isomorphic representation of occupations as producing different

[22]One possible alternative avenue is to note that occupations are not uniformly distributed across industries. Using the industry-based stock price data, as in Loungani, Rush, and Tave (1990) and Brainard and Cutler (1993), we can attempt to infer the implied shocks to occupations. While complicated, such analysis may prove fruitful.

goods and shocks are the shocks to demand for services of different occupations. In particular, assume that each occupation produces a differentiated good and faces a Marshallian demand function $p = p(z, O)$, where p is the relative price of the good and O is the total quantity produced in the occupation. Individuals value not only the product produced in their occupation but also products of all other occupations - e.g. through a CES utility function with a weight assigned to each occupational good. As a result, having produced the good in their occupation, they exchange it for goods produced by the other occupations. Under this scenario, the idiosyncratic shocks z, modeled as a shock to the weights in the utility function can be interpreted as a demand shock (we can instead use also, or only, productivity shocks modeled as a shock to the occupational production function). A higher realization of the shock z in an occupation (higher weight in the utility function) implies that the demand for the services of that occupation has increased. That allows workers in that occupation to charge a higher price for a given level of total output in the occupation and, in return, buy more of the goods produced in the other occupations. Of course, we would expect an inflow of labor and capital into this occupation. Suppose that we have free capital and (to some extent) labor mobility across occupations and a constant returns to scale production function in labor and capital. Then, doubling the amount of capital and labor in the occupation would double output, but since an increase in the output O decreases the price of the product p, the marginal revenue product for an additional worker in that occupation is declining. As a result, the economy behaves as if we had occupations producing the same good but with a decreasing returns to labor technology (and a fixed factor) which is being subject to productivity shocks each period. In fact, the original Lucas and Prescott (1974) paper describes the environment in terms of the above mentioned Marshallian demand functions and performs the analysis by placing the required restriction directly on the revenue function on an island rather than on the production function on that island. Since the two versions of the model are indistinguishable from each other, our choice to work with a more convenient technology representation is inconsequential.

Random Search. We have assumed that search is random in the sense that, for a worker switching occupations, the probability of arriving at a specific occupation is the same across all occupations. An alternative is to assume that search is directed, similar to the original Lucas and Prescott (1974) model. The choice between these to modeling strategies is less important than it may appear. The short model period of two months allows workers to sample as many as six occupations in a given year and quickly locate an occupation with a sufficiently high productivity. Thus, search in our model is directed, but it takes some time for the workers to identify productive occupations. the cost imposed on workers by this imperfection of the search technology is not large. To see this, consider the dispersion in present discounted value of lifetime earnings of inexperienced workers in the model. The 90 to 10 ratio is less than 1.03.[23]

In the directed search version of our model, there will be an equilibrium condition stating that the expected value (not wages) of starting next period in a new occupation as an inexperienced worker is equalized across occupations that are receiving workers. Note that even with fully directed search, the present value of lifetime earnings will not be equalized across all occupations because of the cost of switching. There are occupations with relatively low values of lifetime earnings where nobody chooses to arrive and at the same time nobody decides to leave since the benefit of a higher value of starting in a different occupation is offset by the cost of reallocating.[24]

[23]To see this differently, if we take a worker from the worst occupation in the economy and randomly reallocate her to another occupation, her present value lifetime earnings would increase by only 0.4%.

[24]There is little empirical evidence to guide our choice between a random or directed search model. In

We should emphasize that all the channels we analyze in the random search model are also present in the version of the model with perfectly directed search. The level of wage inequality may be somewhat higher or lower than in the model with random search. Similar to the model with random search, in response to the increase in the variance of the productivity shock process and to the decline in its persistence (needed to generate a higher level of mobility), there will be an increase in wage inequality in the directed search version of the model as well. The endogenous response of workers to the changing economic environment is the same in the two versions of the model. Therefore, even though we have random search in the model, we expect that quantitatively our model does not differ much from a directed search model.

Capital Mobility. We have assumed that while labor is perfectly mobile across occupations, capital is not. Allowing for capital mobility does not change our conclusions. Similar to Veracierto (2002) and Manovskii (2003), assume that there are a large number of competitive firms in each occupation that have access to a production technology:

$$y = F(L, K, z) = zL^{\gamma}K^{\kappa}, \tag{12}$$

where K represents the total amount of capital supplied to the production of output in an occupation, $L = [a_1 g_1^{\rho} + a_2 g_2^{\rho}]^{\frac{1}{\rho}}$, and $\gamma + \kappa \leq 1$. Capital is assumed to be perfectly mobile across occupations, and thus its rental rate, r, is equalized across all occupations. Thus, the amount of capital allocated to an occupation with labor supply L is given by:

$$K = \left[\frac{r}{z\kappa}\right]^{\frac{1}{\kappa-1}} L^{\frac{\gamma}{1-\kappa}}. \tag{13}$$

several waves of the PSID, unemployed individuals were asked to name the two-digit occupation in which they were trying to find a job. Less than 30% of these workers ended up finding a job in the desired occupation, while the large majority of them found a job in a different two-digit occupation. This casts doubt on the assumption of perfectly directed search. The world is probably somewhere in between.

Wages for a worker with experience i are then given by:

$$w_i(L, z; r) = a_i z^{\frac{1}{1-\kappa}} \gamma g_i^{\rho-1} \left[\frac{r}{\kappa}\right]^{\frac{\kappa}{\kappa-1}} L^{\frac{\gamma+\kappa\rho-\rho}{1-\kappa}}. \tag{14}$$

This implies that capital will reallocate toward highly productive occupations, increasing wages of the workers present in those occupations and decreasing wages in less productive occupations. Thus, capital endogenously amplifies the volatility in the occupation-specific productivity shocks, so that with mobile capital in the model we would need a smaller level and a smaller increase in the variance of the shocks to match the facts on occupational mobility. We, however, are not interested in the shock process itself. We calibrate this process to match occupational mobility in both steady-states. In the presence of capital we will get a different process for the genuine z, but the combined effect of that z and the endogenous capital reallocation would lead to the same process for labor productivity that we use in this version of the paper. The interpretation would probably be more natural but, given our calibration strategy, the quantitative results, in particular, the implications for wage inequality, would be unchanged.

Steady-State Analysis. We have concentrated our analysis on two stationary equilibria of the model, one referring to the early 1970s and the other to the mid-1990s. The main problem we face in computing transitions is that we have to take a stand on when the change in the environment occurred and if it was a one-shot change or a continuous process. We do not know the answer to this question. One could calibrate the model to match occupational mobility in every year of the transition and read the implications of the model for the path of wage inequality. This is, however, a very hard computational problem. We are comfortable restricting to the steady-state analysis because occupational mobility and wage inequality were stable in the early 1970s (Rosenfeld (1979) for the former, and Katz and Autor (1999) for the latter) and the mid-1990s (Kambourov and Manovskii (2004b) as well as Moscarini and Vella (2003) for the former, and Card and DiNardo (2002) for the latter) - the periods to which we calibrate our model - and the increase in both variables was concentrated in the relatively short period between the early to mid-1970s and early 1990s.[25]

9 Conclusion

In this paper we argue that wage inequality and occupational mobility are interrelated phenomena. The link between them is motivated with our empirical findings that human capital is occupation-specific and that the fraction of workers switching occupations in the U.S. increased from 16% a year in the early 1970s to 21% in the mid-1990s. We develop a general equilibrium model with occupation-specific human capital and heterogeneous experience of workers within occupations. The model is characterized by endogeneity of wages and occupation separation rates (i.e., endogenous destruction of occupation-specific human capital in the economy). We find that the level of wage inequality in the model is high and close to the observed in the data levels of within-group wage inequality. Further, we find that the model calibrated to match the increase in occupational mobility accounts for almost all of the increase in within-group wage inequality and the decline in wage stability over the period. Using the model, we evaluate several reasons for the increase in occupational mobility and argue that the one consistent with the data is the increase in the variability of productivity shocks to occupations. We describe the particular channels through which increased uncertainty in the economy leads to higher wage inequality. An important friction in the market that we draw attention to is the fact that it takes time to build occupation-specific experience. A distinguishing feature of the theory is that it relies

[25] As Card and DiNardo (2002) show, the fact that wage inequality stabilized in the 1990s poses a problem for the skill-biased technical change hypothesis, since computer technology continued to advance rapidly.

on the observable changes in occupational mobility to accounts for changes in within-group wage inequality and the decline in wage stability.

Table 1: Wage Inequality in the United States, Average Population Structure.

	1970-73	1993-96
Variance of log wages		
Overall	0.225	0.354
Within-Group 1	0.162	0.248
Within-Group 2	0.177	0.293
Log 90/10 ratio		
Overall	1.167	1.448
Within-Group 1	0.975	1.192
Within-Group 2	0.999	1.293
Gini coefficient		
Overall	0.258	0.346
Within-Group 1	0.215	0.273
Within-Group 2	0.223	0.299

Note - Authors' calculations from the PSID. The sample is restricted to male heads of household, aged 23-61, who are not self- or dual-employed, and who are not working for the government. In addition, we drop in each year (i) all observations with a nominal hourly wage which is lower than half the minimum wage in that year, and (ii) all observations which report less than 520 hours worked in that year.

Table 2: Wage Stability in the United States, Average Population Structure.

Average $var(\eta_i)$	1970-78	1988-96
Overall	0.087	0.175
Within-Group 1	0.086	0.173
Within-Group 2	0.126	0.207

Note - Authors' calculations from the PSID. $var(\eta_i)$ denotes the average (across individuals) variance of transitory wages. See Section 2.1.2 for details.

Table 3: Changes in the U.S. Labor Market: Occupational Mobility.

	1970-73	1993-96	Change
Actual Population Structure	0.157	0.205	30.6%
Average Population Structure	0.159	0.213	34.0%

Note - Authors' calculations from the PSID. Occupational mobility refers to the average annual rate of occupational mobility at the three-digit level over the corresponding period. See Kambourov and Manovskii (2004b) for details.

Table 4: Occupational Specificity of Human Capital.

	Returns to Experience			
	OLS		IV-GLS	
	2 years	5 years	2 years	5 years
Occupation	.0891	.1995	.0539	.1197
	(.0082)	(.0186)	(.0068)	(.0153)
Industry	-.0109	-.0306	-.0020	-.0064
	(.0081)	(.0170)	(.0071)	(.0149)
Employer	.0010	-.0106	.0008	.0019
	(.0136)	(.0149)	(.0095)	(.0136)

Source: Kambourov and Manovskii (2002). Returns to experience represent the percentage increase in wages due to the first 2, 5, or 10 years of occupational, industry, or employer tenure. Standard errors are in parentheses. The results are computed from the estimates of the following econometric model:

$$\begin{aligned}\ln w_{ijmnt} &= \beta_0 Emp\_Ten_{ijt} + \beta_1 OJ_{ijt} + \beta_2 Occ\_Ten_{imt} + \beta_3 Ind\_Ten_{int} \\ &\quad + \beta_4 Work\_Exp_{it} + \mu_i + \lambda_{ij} + \xi_{im} + \upsilon_{in} + \epsilon_{it},\end{aligned}$$

where w_{ijmnt} is the real hourly wage of person i working in period t with employer j in occupation m and industry n. Emp_Ten, Occ_Ten, and Ind_Ten denote tenure with the current employer, occupation, and industry, respectively. OJ is a dummy variable that equals one if the individual is not in the first year with the current employer. $Work\_Exp$ denotes overall labor market experience. The regression includes an individual-specific component μ_i, a job-match component λ_{ij}, an occupation-match component ξ_{im}, and an industry-match component υ_{in}. Other variables in the regression include an intercept term, one-digit occupation and industry dummies, a union dummy, a marital status dummy, year dummies, region dummies, education, as well as unemployment rate and lagged unemployment rate in the county of residence. The model also contains the square term of employer tenure and education, and the square and cube terms of occupation and industry tenure and overall work experience. The model is estimated using OLS and an IV-GLS procedure proposed by Altonji and Shakotko (1987).

Table 5: Calibrated Values of Time-Invariant Parameters.

δ	γ	β	a	ρ	p
0.0042	0.68	0.9935	0.44	0.73	0.0167

Table 6: Calibrated Values of Time-Dependent Parameters.

Parameter	1970-73	1993-96
ϕ	0.918	0.878
σ_ϵ	0.180	0.291
θ	0.454	0.608
α	0.000	-0.115

ϕ - persistence of the log shocks.
σ_ϵ - standard deviation of the white noise.
θ - standard deviation of the log shocks.
α - unconditional mean of the process.

Table 7: Matching the Calibration Targets.

	Target	1970-73		1993-96	
		Data	Model	Data	Model
1.	3d occupational mobility	0.159	0.159	0.213	0.213
2.	The average number of switches for those who switched a 3-digit occupation at least once in a 4-year period	1.54	1.54	1.71	1.71

Note - The table describes the performance of the model in matching the targets. The data are computed by the authors from the PSID.

Table 8: Shock Values and the Stationary Distribution of Occupations over Shocks.

	1970-73		1993-96	
	z	$\zeta(z)$	z	$\zeta(z)$
1.	0.256	0.004	0.143	0.003
2.	0.311	0.008	0.186	0.008
3.	0.378	0.020	0.241	0.019
4.	0.459	0.043	0.313	0.042
5.	0.558	0.077	0.406	0.076
6.	0.677	0.117	0.527	0.117
7.	0.823	0.150	0.683	0.152
8.	1.000	0.162	0.887	0.166
9.	1.215	0.150	1.151	0.152
10.	1.476	0.117	1.494	0.117
11.	1.794	0.077	1.939	0.076
12.	2.179	0.043	2.516	0.042
13.	2.648	0.020	3.266	0.019
14.	3.217	0.008	4.238	0.008
15.	3.908	0.004	5.500	0.003

z - values of the shocks.
$\zeta(z)$ - stationary distribution of occupations over shocks.

Table 9: Results from the Calibrated Model: The Level of Wage Inequality and Wage Stability, 1970-1973.

	Model	Data		
		Within-Group 2	Within-Group 1	Overall
Variance of log wages	0.120	0.177	0.162	0.225
Log 90/10 ratio	0.854	0.999	0.975	1.167
Gini coefficient	0.198	0.223	0.215	0.258
Variance of transitory log wages	0.096	0.126	0.086	0.087

Note - In the data, the variance of transitory log wages is computed for the 1970-1978 period.

Table 10: The Importance of Human Capital, 1970-1973 Period.

	Occupational Mobility	Variance of Logs
Benchmark	0.159	0.120
No human capital	0.326	0.069
No human capital: recalibrated	0.159	0.030

Table 11: Comparative Statics, 1970-1973.

	Benchmark	a=0.40	a=0.48	ρ=0.60	ρ=0.85	p=0.0133	p=0.0233	γ=0.56	γ=0.80
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Occupational mobility:									
	0.159	0.102	0.211	0.166	0.141	0.156	0.166	0.149	0.180
Variance of log wages:									
	0.120	0.149	0.101	0.126	0.118	0.124	0.115	0.114	0.137
Log 90/10 ratio:									
	0.854	0.955	0.762	0.872	0.848	0.864	0.844	0.830	0.911
Gini coefficient:									
	0.198	0.220	0.184	0.203	0.197	0.201	0.196	0.194	0.211
Variance of transitory log wages:									
	0.096	0.110	0.086	0.102	0.093	0.099	0.092	0.091	0.114

Note - Column (1) reports the statistics in the benchmark calibration of the model for the period 1970-73 in which $a = 0.44$, $\rho = 0.73$, $p = 0.0167$, and $\gamma = 0.68$. The rest of the table reports how the statistics change if we keep all parameters at their benchmark-calibrated values in that period and one by one increase or decrease the values of a, ρ, p, and γ.

Table 12: Results from the Calibrated Model: The Increase in Wage Inequality and the Decline in Wage Stability.

	Model	Data		
		Within-Group2	Within-Group1	Overall
Variance of log wages				
1970-1973	0.120	0.177	0.162	0.225
1993-1996	0.231	0.293	0.248	0.354
Log 90/10 ratio				
1970-1973	0.854	0.999	0.975	1.167
1993-1996	1.185	1.293	1.192	1.448
Gini coefficient				
1970-1973	0.198	0.223	0.215	0.258
1993-1996	0.273	0.299	0.273	0.346
Variance of transitory log wages				
1970-1978	0.096	0.126	0.086	0.087
1988-1996	0.181	0.207	0.173	0.175

Table 13: Recalibrating the Model with Different Estimates of a, ρ, and p.

	a=0.41, ρ=0.85, p=0.0208		a=0.48, ρ=0.60, p=0.0139	
	1970-73	1993-96	1970-73	1993-96
Variance of log wages	0.135	0.273	0.077	0.165
Log 90/10 ratio	0.916	1.282	0.665	0.989
Gini coefficient	0.214	0.297	0.160	0.231
Variance of transitory log wages	0.107	0.226	0.062	0.132

Note - In the benchmark calibration of the model $p = 0.0167$, implying that it takes 10 years to become experienced in an occupation. This table reports the behavior of the model if the value of p is changed. In the first case, the value of p implies that it takes, on average, eight years to become experienced in an occupation. In the second case, the value of p implies that one becomes experienced in an occupation after 12 years. In each of the cases, given p, we reestimate the values of a and ρ as described in Appendix II, and then recalibrate the parameters governing the occupational shock process.

Table 14: The Effects of a Decline in the Cost of Search.

	1970-73 (1)	1993-96 (2)
Variance of log wages	0.120	0.110
Log 90/10 ratio	0.854	0.795
Gini coefficient	0.198	0.189
Variance of transitory log wages	0.096	0.086

	1970-73 (1)	1993-96 (2)	LCS Model (3)
Occupational mobility	0.159	0.213	0.238
The average number of switches for those who switched a 3-digit occupation at least once in a 4-year period	1.54	1.71	1.86

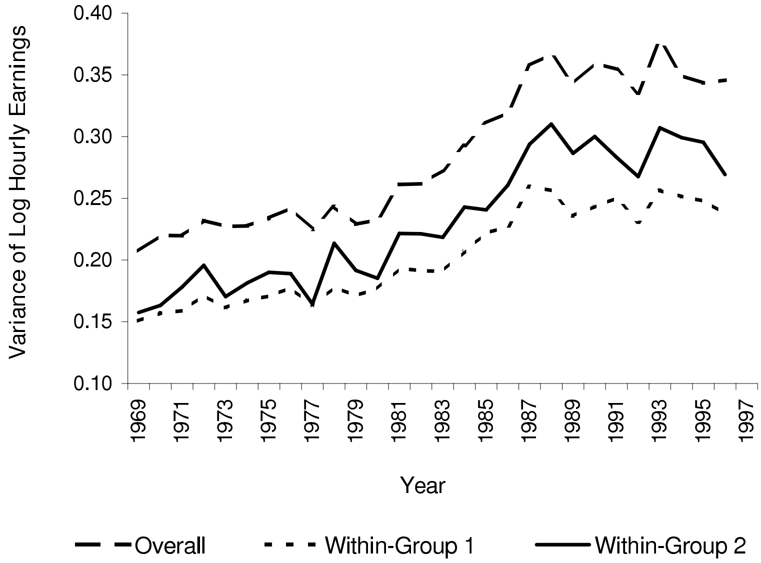
Note - The table reports the results of an experiment in which after the model is calibrated to the performance of the economy in the 1970-73 period, the cost of search is reduced by half. Column (1) in the top panel shows statistics for the economy calibrated to the 1970-73 period. The levels of these statistics after the cost of search is reduced are described in column (2). Column (1) in the bottom panel shows the level of the targets in the 1970-73 period, while column (2) shows their level in the 1993-96 period. Column (3) describes the level of these variables after the cost of search is reduced by half in the model.

Table 15: Between-Occupation and Within-Occupation Wage Inequality: Variance of Log Wages, Three-Digit Level.

	1970-73	1993-96
Overall		
Between-occupation	0.099	0.192
Within-occupation	0.127	0.154
Within-Group 1		
Between-occupation	0.058	0.108
Within-occupation	0.112	0.148
Within-Group 2		
Between-occupation	0.067	0.141
Within-occupation	0.109	0.140

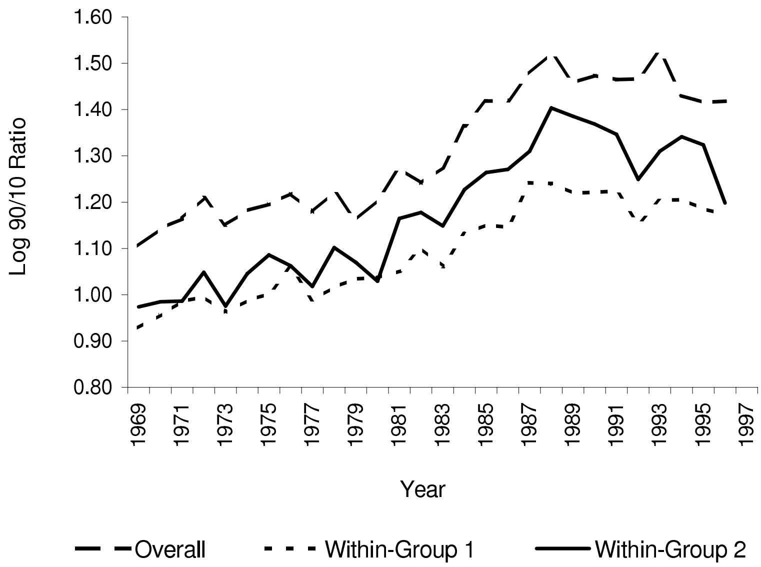
Note - Between-occupation wage inequality is measured as the variance of the mean log wages in an occupation while within-occupation inequality is the average (across all occupations) variance of log wages within an occupation. We use the PSID and the sample is restricted to male household heads, aged 23-61, who are not self- or dual-employed, are not working for the government, and have worked at least 520 hours during the year. Each year we restrict to occupations which have at least four observations in that year.

Figure 1: Variance of Log Real Hourly Earnings in the United States, 1969-1997, PSID, Average Population Structure.



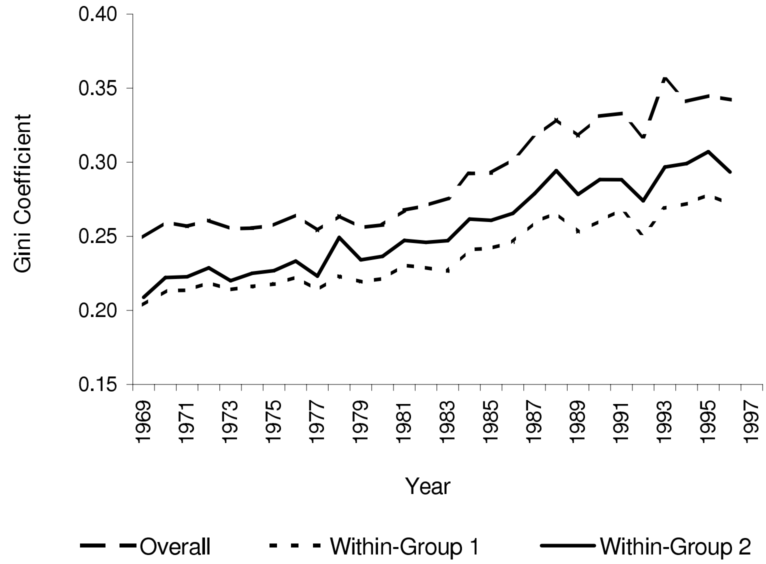
Source: Authors' calculations from the PSID.

Figure 2: Log 90/10 Ratio of Real Hourly Earnings in the United States, 1969-1997, PSID, Average Population Structure.



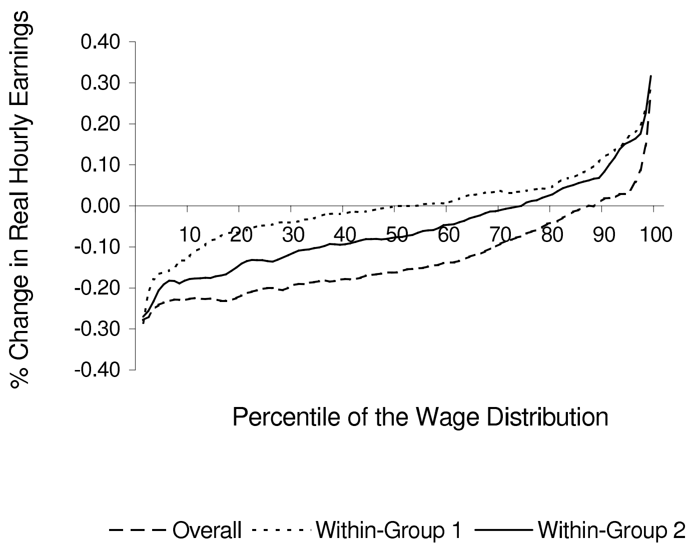
Source: Authors' calculations from the PSID.

Figure 3: Gini Coefficient of Real Hourly Earnings in the United States, 1969-1997, PSID, Average Population Structure.



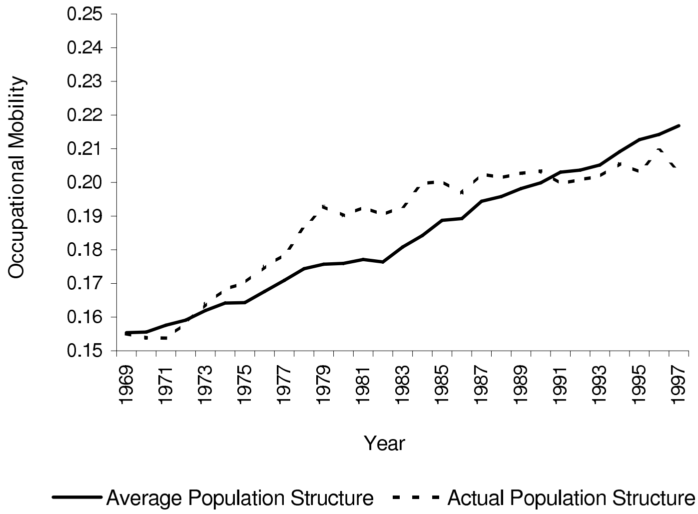
Source: Authors' calculations from the PSID.

Figure 4: Percentage Change in Real Hourly Earnings by Percentiles of the Wage Distribution, 1993 vs. 1970, Average Population Structure.



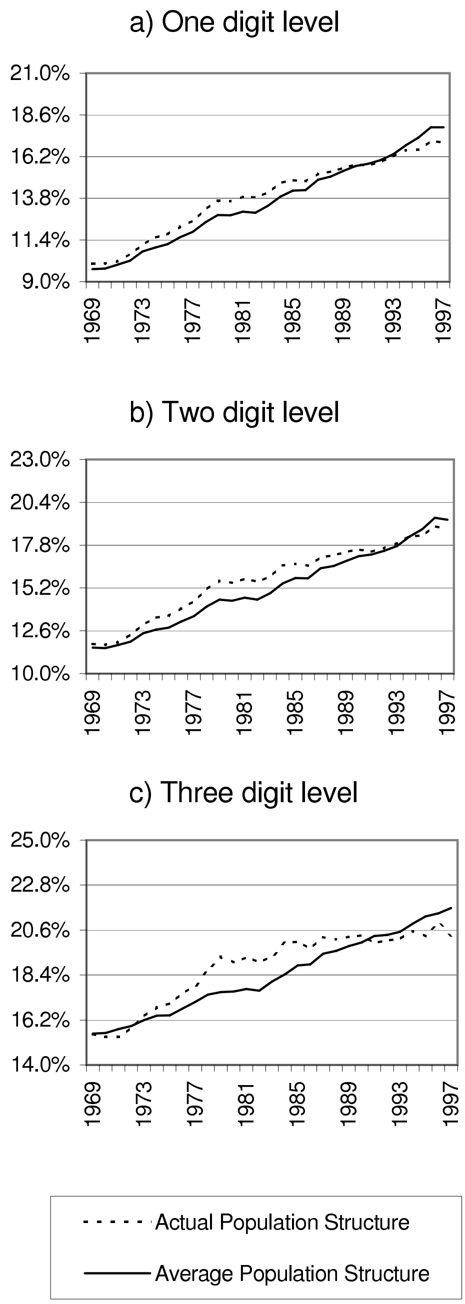
Source: Authors' calculations from the PSID.

Figure 5: Occupational Mobility in the United States, 1969-1997, Three Digit Level.



Source: Kambourov and Manovskii (2004b).

Figure 6: Occupational Mobility in the United States, 1969-1997.



Source: Kambourov and Manovskii (2004b).

Figure 7: Percentage Change in Real Hourly Earnings by Percentiles of the Wage Distribution, 1993 vs. 1970, Model vs. Data.

Note - The graph for the data represents the percentage change in real hourly earnings by percentiles using the *Within-Group 2* measure of wages and average population structure. Figures 4 and A-4 show the corresponding graphs for the other measures of wages and the actual population structure.

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APPENDICES

I Facts on the Actual Population Structure

Table A-1: Wage Inequality in the United States, Actual Population Structure.

	1970-73	1993-96
Variance of logs		
Overall	0.225	0.367
Within-Group 1	0.161	0.264
Within-Group 2	0.176	0.305
Log 90/10 ratio		
Overall	1.171	1.473
Within-Group 1	0.977	1.223
Within-Group 2	1.009	1.336
Gini coefficient		
Overall	0.257	0.351
Within-Group 1	0.214	0.280
Within-Group 2	0.223	0.306

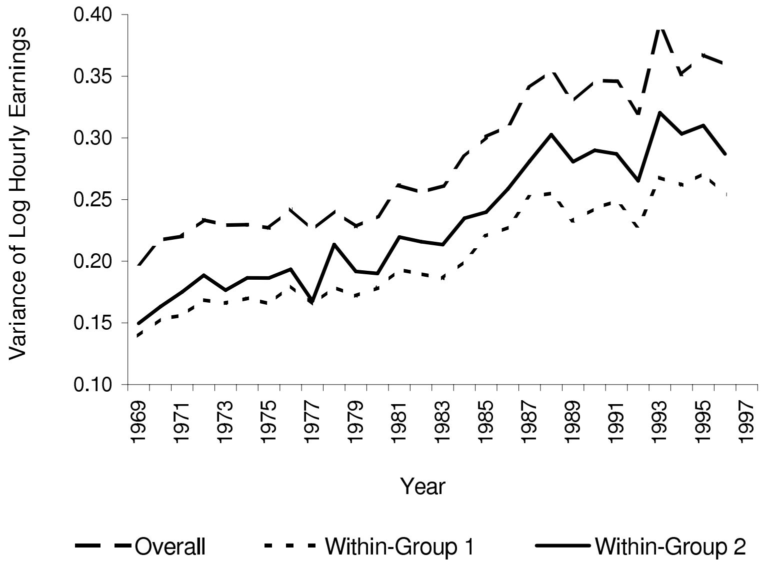
Note - Authors' calculations from the PSID. The sample is restricted to male heads of household, aged 23-61, who are not self- or dual-employed, and who are not working for the government. In addition, we drop in each year (i) all observations with a nominal hourly wage which is lower than half the minimum wage in that year, and (ii) all observations which report less than 520 hours worked in that year.

Table A-2: Wage Stability in the United States, Actual Population Structure.

Average $var(\eta_i)$	1970-78	1988-96
Overall	0.087	0.190
Within-Group 1	0.087	0.188
Within-Group 2	0.124	0.221

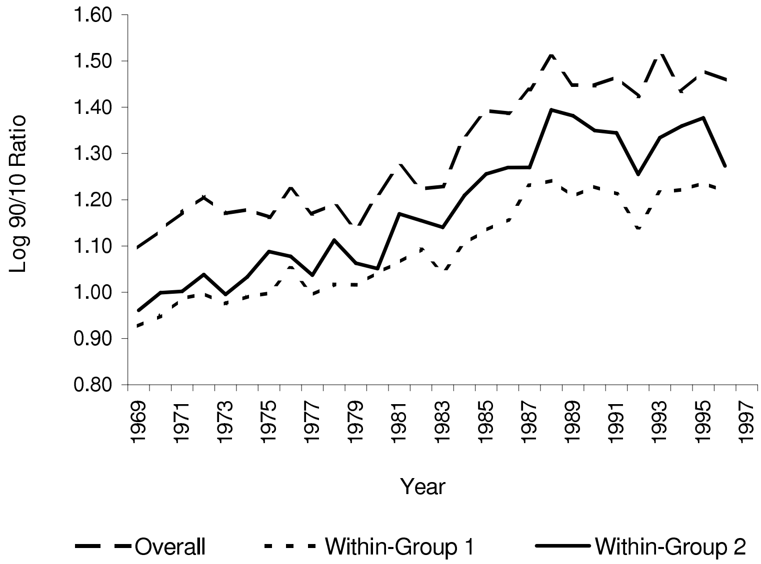
Note - Authors' calculations from the PSID. $var(\eta_i)$ denotes the average (across individuals) variance of transitory wages. See Section 2.1.2 for details.

Figure A-1: Variance of Log Real Hourly Earnings in the United States, 1969-1997, PSID, Actual Population Structure.



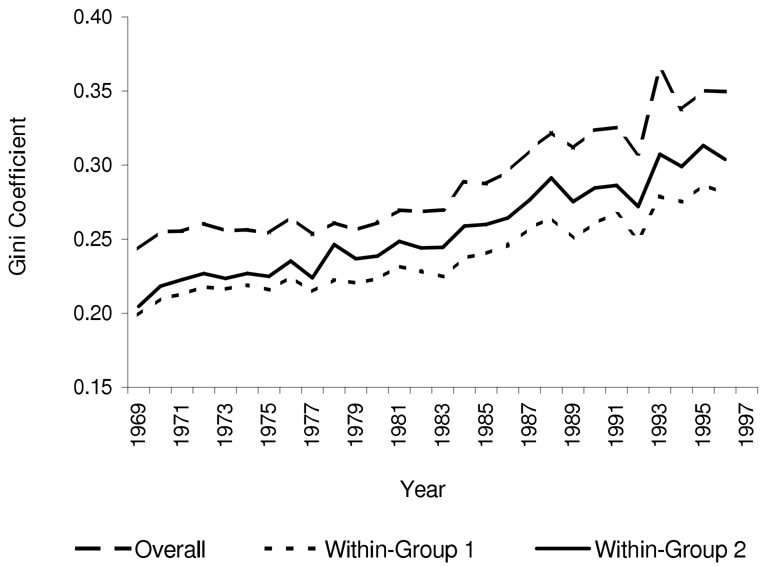
Source: Authors' calculations from the PSID.

Figure A-2: Log 90/10 Ratio of Real Hourly Earnings in the United States, 1969-1997, PSID, Actual Population Structure.



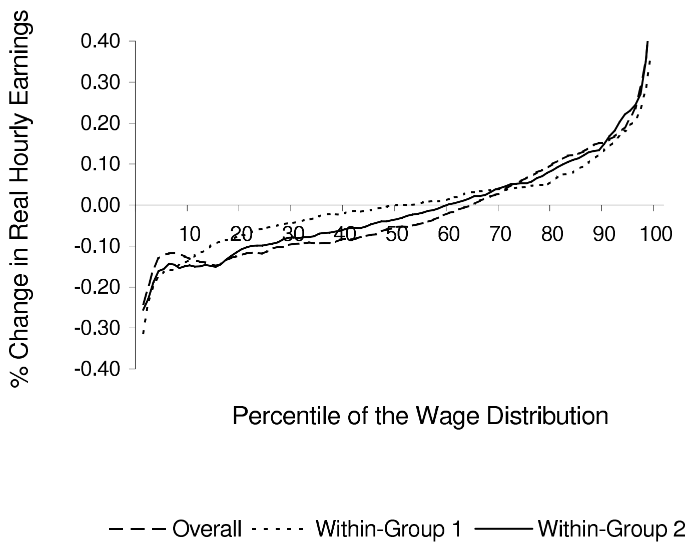
Source: Authors' calculations from the PSID.

Figure A-3: Gini Coefficient of Real Hourly Earnings in the United States, 1969-1997, PSID, Actual Population Structure.



Source: Authors' calculations from the PSID.

Figure A-4: Percentage Change in Real Hourly Earnings by Percentiles of the Wage Distribution, 1993 vs. 1970, Actual Population Structure.



Source: Authors' calculations from the PSID.

II Estimating the Production Function Parameters

In this appendix, we discuss the estimation procedure for a and ρ. We postulate the following regression model:

$$\ln\left(\frac{w_2}{w_1}\right)_{it} = \xi_0 + \xi_1 \ln\left(\frac{g_2}{g_1}\right)_{it} + \nu_{it}, \tag{A1}$$

where i indexes occupations and t indexes time. Further, w_1 and w_2 denote the wages that inexperienced and experienced workers receive in occupation i in period t, while g_1 and g_2 denote the number of inexperienced and experienced workers.

The way individuals are classified into inexperienced and experienced in an occupation is conditional on our choice of the parameter p - the probability of an inexperienced worker becoming experienced. Given p, it takes, on average, $x = \frac{1}{p}$ periods for an individual to become experienced in an occupation. For instance in the benchmark case, $p = 0.0167$ implying that x is 60 periods (or 10 years since the model period is two months). Therefore, in the benchmark case, we considered workers to be experienced if their occupational tenure is over 10 years. In the cases when we consider a different value for the parameter p, we also change the value of x accordingly and our interpretation of inexperienced and experienced workers. The same cut-off point is used for all occupations.

We construct workers' tenure in an occupation in the following way. We allow individuals into the sample after they either switch an occupation for the first time or accumulate more than $\frac{x}{2}$ years of occupational experience.[26] Upon an occupational switch, a worker's occupational tenure is set to zero. From then on, if a worker is employed in the current year, does not switch her occupation, and reports to have worked more than 1000 hours during

[26] It is not possible to determine the exact occupation tenure of individuals who appear for the first time in the sample, for individuals who occasionally drop out from the survey, or for individuals who change their head-of-household status in some years. These are followed until they switch their occupation or until they accumulate enough tenure in the current one to ensure that they could be considered experienced, and only then they are included in the experiments.

the previous year, her occupational tenure is increased by 12 months. If she reports to be unemployed this year or reports less than 1000 hours worked in the previous year, her occupation tenure remains unchanged.[27] The switches are identified using the Retrospective Files during 1968-1980 and the originally coded data after 1980. Following Kambourov and Manovskii (2002), on the original data we consider an occupation switch to be a genuine one if there is a corresponding position or employer switch. If an individual reports a new occupation but does not indicate a position or an employer change, no occupation switch is considered to have occurred.

To eliminate the effect on wages of variables that are not explicitly modeled we first run an OLS regression of wages on overall labor market experience (a linear, quadratic, and cubic term), education (a linear and quadratic term), region of residence, marital status, union status, year, and current and last year's level of unemployment in the county of residence. The effect of these variables is subtracted from observed wages.

Finally, given our partition of the sample into experienced and inexperienced workers in each occupation, we compute $(w_2/w_1)_{it}$ and $(g_2/g_1)_{it}$, for each occupation i in every year t. We consider only occupations that have at least five experienced as well as five inexperienced individuals in a given year.

The regression model A1 is then estimated using ordinary least squares.

[27] The results are robust to our choice of 1000 hours cut-off.

III Computational Algorithm

1. Guess S and V^s.

2. Define a grid of points on (ψ_1, ψ_2, z).

3. Guess a function $V_1^0(\psi_1, \psi_2, z)$ that is (weakly) decreasing and (weakly) convex in ψ_1, a function $V_2^0(\psi_1, \psi_2, z)$ that is (weakly) decreasing and (weakly) convex in ψ_2, and a function $H^0(\psi_1, \psi_2, z)$ that is (weakly) increasing in ψ_1 and ψ_2.

4. For each point on the (ψ_1, ψ_2, z) grid, find the optimal policies g_1 and g_2 in the following way. Set $G = (\psi_1, \psi_2)$. Then,

   (a) If both $V_1(\psi_1, \psi_2, z) \geq V^s$ and $V_2(\psi_1, \psi_2, z) \geq V^s$, everybody present in the occupation will choose to stay and thus $g_1 = \psi_1$ and $g_2 = \psi_2$ is a consistent policy. Go to 5.

   (b) If the condition in (a) is not satisfied, then

      i. Set $G = (\bar{g_1}, \psi_2)$, where $\bar{g_1}$ solves the following equation:

      $$\begin{aligned} &z\gamma a\bar{g_1}^{\rho-1}\left[a\bar{g_1}^{\rho} + (1-a)\psi_2^{\rho}\right]^{\frac{\gamma-\rho}{\rho}} + \\ &\beta(1-p)\sum_{z'} V_1(\delta + (1-\delta)(S + (1-p)\bar{g_1}), (1-\delta)(p\bar{g_1} + \psi_2), z')Q(z, z') + \\ &\beta p\sum_{z'} V_2(\delta + (1-\delta)(S + (1-p)\bar{g_1}), (1-\delta)(p\bar{g_1} + \psi_2), z')Q(z, z') = V^s. \end{aligned}$$

      Check whether under this policy $V_2(\psi_1, \psi_2, z) \geq V^s$ and whether $\bar{g_1}$ is feasible. If not, then this G cannot be a consistent policy. If yes, then G is a candidate for the optimal policy.

      ii. Set $G = (\psi_1, \bar{g_2})$, where $\bar{g_2}$ solves the following equation:

      $$z\gamma(1-a)\bar{g_2}^{\rho-1}\left[a\psi_1^{\rho} + (1-a)\bar{g_2}^{\rho}\right]^{\frac{\gamma-\rho}{\rho}} +$$

$$\beta \sum_{z'} V_2(\delta + (1-\delta)(S + (1-p)\psi_1), (1-\delta)(p\psi_1 + \bar{g_2}), z')Q(z, z') = V^s$$

Check whether under this policy $V_1(\psi_1, \psi_2, z) \geq V^s$ and whether $\bar{g_2}$ is feasible. If not, then this G cannot be a consistent policy. If yes, then G is a candidate for the optimal policy.

iii. Set $G = (\bar{g_1}, \bar{g_2})$ where $\bar{g_1}$ and $\bar{g_2}$ jointly solve the equations in i and ii above. Check whether $\bar{g_1}$ and $\bar{g_2}$ are feasible. If not, then this G cannot be a consistent policy. If yes, then G is a candidate for the optimal policy.

iv. The optimal policy is a candidate policy from the previous three cases that maximizes the value function $H(\psi_1, \psi_2, z)$[28], where

$$H(\psi, z) = \max \left\{ z \left[a g_1^{\rho} + (1-a) g_2^{\rho} \right]^{\gamma/\rho} + \beta \sum_{z'} H(\psi', z')Q(z, z') \right\}$$

5. Given the optimal policy $G = (g_1, g_2)$ obtained above, update the value functions and get $V_1^1(\psi_1, \psi_2, z)$, $V_2^1(\psi_1, \psi_2, z)$, and $H^1(\psi_1, \psi_2, z)$.

6. Use V_1, V_2, and H obtained above as the new guess in step 3.

7. Repeat steps 4 through 6 until the policy and value functions converge.

8. Simulate a large number of occupations until the distribution of occupations generates an invariant V^s and S, scaling the economy at each iteration to have measure one of individuals.

9. Compare the obtained V^s and S with the initial guess in 1. If they are the same, stop. If not, make a new guess in 1 that is a convex combination of the previous guess and the simulated values.

[28]This procedure chooses the equilibrium that maximizes the expected present discounted value of production in an occupation or, alternatively, total wages and the returns to the (unobserved) fixed factor.

IV Three-Digit Occupational Codes

PROFESSIONAL, TECHNICAL,
AND KINDRED WORKERS[29]

001 Accountants
002 Architects

Computer specialists

003 Computer programmers
004 Computer systems analysts
005 Computer specialists, not elsewhere classified

Engineers

006 Aeronautical and astronautical engineers
010 Chemical engineers
011 Civil engineers
012 Electrical and electronic engineers
013 Industrial engineers
014 Mechanical engineers
015 Metallurgical and materials engineers
020 Mining engineers
021 Petroleum engineers
022 Sales engineers
023 Engineers, not elsewhere classified
024 Farm management advisors
025 Foresters and conservationists
026 Home management advisors

Lawyers and judges

030 Judges
031 Lawyers

Librarians, archivists, and curators

032 Librarians
033 Archivists and curators

Mathematical specialists

034 Actuaries
035 Mathematicians
036 Statisticians

Life and physical scientists

042 Agricultural scientists
043 Atmospheric and space scientists
044 Biological scientists
045 Chemists
051 Geologists
052 Marine scientists
053 Physicists and astronomers
054 Life and physical scientists, not elsewhere classified
055 Operations and systems researchers and analysts
056 Personnel and labor relations workers

Physicians, dentists, and related practitioners

061 Chiropractors
062 Dentists
063 Optometrists
064 Pharmacists
065 Physicians, medical and osteopathic
071 Podiatrists
072 Veterinarians
073 Health practitioners, not elsewhere classified

Nurses, dietitians, and therapists

074 Dietitians
075 Registered nurses
076 Therapists

Health technologists and technicians

080 Clinical laboratory technologists and technicians
081 Dental hygienists
082 Health record technologists and technicians
083 Radiologic technologists and technicians
084 Therapy assistants
085 Health technologists and technicians, not elsewhere classified

Religious workers

086 Clergymen
090 Religious workers, not elsewhere classified

Social scientists

091 Economists
092 Political scientists
093 Psychologists
094 Sociologists
095 Urban and regional planners
096 Social scientists, not elsewhere classified

Social and recreation workers

100 Social workers
101 Recreation workers

Teachers, college and university

102 Agriculture teachers
103 Atmospheric, earth, marine, and space teachers
104 Biology teachers
105 Chemistry teachers

[29] Source: PSID wave XIV - 1981 documentation, Appendix 2: Industry and Occupation Codes.

110 Physics teachers
111 Engineering teachers
112 Mathematics teachers
113 Health specialties teachers
114 Psychology teachers
115 Business and commerce teachers
116 Economics teachers
120 History teachers
121 Sociology teachers
122 Social science teachers, not elsewhere classified
123 Art, drama, and music teachers
124 Coaches and physical education teachers
125 Education teachers
126 English teachers
130 Foreign language teachers
131 Home economics teachers
132 Law teachers
133 Theology teachers
134 Trade, industrial, and technical teachers
135 Miscellaneous teachers, college and university
140 Teachers, college and university, subject not specified

Teachers, except college and university
141 Adult education teachers
142 Elementary school teachers
143 Prekindergarten and kindergarten teachers
144 Secondary school teachers
145 Teachers, except college and university, not elsewhere classified

Engineering and science technicians
150 Agriculture and biological technicians, except health
151 Chemical technicians
152 Draftsmen
153 Electrical and electronic engineering technicians
154 Industrial engineering technicians
155 Mechanical engineering technicians
156 Mathematical technicians
161 Surveyors
162 Engineering and science technicians, not elsewhere classified

Technicians, except health, and engineering and science
163 Airplane pilots
164 Air traffic controllers
165 Embalmers
170 Flight engineers
171 Radio operators
172 Tool programmers, numerical control
173 Technicians, not elsewhere classified
174 Vocational and educational counselors

Writers, artists, and entertainers
175 Actors
180 Athletes and kindred workers
181 Authors
182 Dancers
183 Designers
184 Editors and reporters
185 Musicians and composers
190 Painters and sculptors
191 Photographers
192 Public relations men and publicity writers
193 Radio and television announcers
194 Writers, artists, and entertainers, not elsewhere classified
195 Research workers, not specified

MANAGERS AND ADMINISTRATORS, EXCEPT FARM
201 Assessors, controllers, and treasurers; local public administration
202 Bank officers and financial managers
203 Buyers and shippers, farm products
205 Buyers, wholesale and retail trade
210 Credit men
211 Funeral directors
212 Health administrators
213 Construction inspectors, public administration
215 Inspectors, except construction, public administration
216 Managers and superintendents, building
220 Office managers, not elsewhere classified
221 Officers, pilots, and pursers; ship
222 Officials and administrators; public administration, not elsewhere classified
223 Officials of lodges, societies, and unions
224 Postmasters and mail superintendents
225 Purchasing agents and buyers, not elsewhere classified
226 Railroad conductors
230 Restaurant, cafeteria, and bar managers
231 Sales managers and department heads, retail trade
233 Sales managers, except retail trade
235 School administrators, college
240 School administrators, elementary and secondary
245 Managers and administrators, not elsewhere classified

SALES WORKERS
260 Advertising agents and salesmen
261 Auctioneers
262 Demonstrators
264 Hucksters and peddlers
265 Insurance agents, brokers, and underwriters
266 Newsboys
270 Real estate agents and brokers
271 Stock and bond salesmen
280 Salesmen and sales clerks, not elsewhere classified

Salesmen were divided into 5 categories dependent on industry. The industry codes are shown in parentheses.
281 Sales representatives, manufacturing industries (Ind. 107-399)
282 Sales representatives, wholesale trade (Ind. 017-058, 507-599)
283 Sales clerks, retail trade (Ind. 608-699 except 618, 639, 649, 667, 668, 688)
284 Salesmen, retail trade (Ind. 607, 618, 639, 649, 667, 668, 688)
285 Salesmen of services and construction (Ind. 067-078, 407-499, 707-947)

CLERICAL AND KINDRED WORKERS
301 Bank tellers
303 Billing clerks
305 Bookkeepers
310 Cashiers
311 Clerical assistants, social welfare
312 Clerical supervisors, not elsewhere classified
313 Collectors, bill and account
314 Counter clerks, except food
315 Dispatchers and starters, vehicle
320 Enumerators and interviewers
321 Estimators and investigators, not elsewhere classified
323 Expediters and production controllers
325 File clerks
326 Insurance adjusters, examiners, and investigators
330 Library attendants and assistants
331 Mail carriers, post office
332 Mail handlers, except post office
333 Messengers and office boys
334 Meter readers, utilities

Office machine operators
341 Bookkeeping and billing machine operators
342 Calculating machine operators
343 Computer and peripheral equipment operators
344 Duplicating machine operators
345 Key punch operators
350 Tabulating machine operators
355 Office machine operators, not elsewhere classified
360 Payroll and timekeeping clerks
361 Postal clerks
362 Proofreaders
363 Real estate appraisers
364 Receptionists

Secretaries
370 Secretaries, legal
371 Secretaries, medical
372 Secretaries, not elsewhere classified
374 Shipping and receiving clerks
375 Statistical clerks
376 Stenographers
381 Stock clerks and storekeepers
382 Teacher aides, except school monitors
383 Telegraph messengers
384 Telegraph operators
385 Telephone operators
390 Ticket, station, and express agents
391 Typists
392 Weighers
394 Miscellaneous clerical workers
395 Not specified clerical workers

CRAFTSMEN AND KINDRED WORKERS
401 Automobile accessories installers
402 Bakers
403 Blacksmiths
404 Boilermakers
405 Bookbinders
410 Brickmasons and stonemasons
411 Brickmasons and stonemasons, apprentices
412 Bulldozer operators
413 Cabinetmakers
415 Carpenters
416 Carpenter apprentices
420 Carpet installers
421 Cement and concrete finishers
422 Compositors and typesetters
423 Printing trades apprentices, except pressmen
424 Cranemen, derrickmen, and hoistmen
425 Decorators and window dressers
426 Dental laboratory technicians
430 Electricians
431 Electrician apprentices
433 Electric power linemen and cablemen
434 Electrotypers and stereotypers
435 Engravers, except photoengravers
436 Excavating, grading, and road machine operators, except bulldozer
440 Floor layers, except tile setters
441 Foremen, not elsewhere classified
442 Forgemen and hammermen
443 Furniture and wood finishers
444 Furriers
445 Glaziers
446 Heat treaters, annealers, and temperers
450 Inspectors, scalers, and graders; log and lumber
452 Inspectors, not elsewhere classified
453 Jewelers and watchmakers
454 Job and die setters, metal
455 Locomotive engineers
456 Locomotive firemen
461 Machinists
462 Machinist apprentices

Mechanics and repairmen
470 Air conditioning, heating, and refrigeration

471 Aircraft
472 Automobile body repairmen
473 Automobile mechanics
474 Automobile mechanic apprentices
475 Data processing machine repairmen
480 Farm implement
481 Heavy equipment mechanics, including diesel
482 Household appliance and accessory installers and mechanics
483 Loom fixers
484 Office machine
485 Radio and television
486 Railroad and car shop
491 Mechanic, except auto, apprentices
492 Miscellaneous mechanics and repairmen
495 Not specified mechanics and repairmen
501 Millers; grain, flour, and feed
502 Millwrights
503 Molders, metal
504 Molder apprentices
505 Motion picture protectionists
506 Opticians, and lens grinders and polishers
510 Painters, construction and maintenance
511 Painter apprentices
512 Paperhangers
514 Pattern and model makers, except paper
515 Photoengravers and lithographers
516 Piano and organ tuners and repairmen
520 Plasterers
521 Plasterer apprentices
522 Plumbers and pipe fitters
523 Plumber and pipe fitter apprentices
525 Power station operators
530 Pressmen and plate printers, printing
531 Pressman apprentices
533 Rollers and finishers, metal
534 Roofers and slaters
535 Sheetmetal workers and tinsmiths
536 Sheetmetal apprentices
540 Shipfitters
542 Shoe repairmen
543 Sign painters and letterers
545 Stationary engineers
546 Stone cutters and stone carvers
550 Structural metal craftsmen
551 Tailors
552 Telephone installers and repairmen
554 Telephone linemen and splicers
560 Tile setters
561 Tool and die makers
562 Tool and die maker apprentices
563 Upholsterers
571 Specified craft apprentices, not elsewhere classified
572 Not specified apprentices
575 Craftsmen and kindred workers, not elsewhere classified

ARMED FORCES
600 Members of armed forces

OPERATIVES, EXCEPT TRANSPORT
601 Asbestos and insulation workers
602 Assemblers
603 Blasters and powdermen
604 Bottling and canning operatives
605 Chainmen, rodmen, and axmen; surveying
610 Checkers, examiners, and inspectors; manufacturing
611 Clothing ironers and pressers
612 Cutting operatives, not elsewhere classified
613 Dressmakers and seamstresses, except factory
614 Drillers, earth
615 Dry wall installers and lathers
620 Dyers
621 Filers, polishers, sanders, and buffers
622 Furnacemen, smeltermen, and pourers
623 Garage workers and gas station attendants
624 Graders and sorters, manufacturing
625 Produce graders and packers, except factory and farm
626 Heaters, metal
630 Laundry and dry cleaning operatives, not elsewhere classified
631 Meat cutters and butchers, except manufacturing
633 Meat cutters and butchers, manufacturing
634 Meat wrappers, retail trade
635 Metal platers
636 Milliners
640 Mine operatives, not elsewhere classified
641 Mixing operatives
642 Oilers and greasers, except auto
643 Packers and wrappers,except meat and produce
644 Painters, manufactured articles
645 Photographic process workers

Precision machine operatives
650 Drill press operatives
651 Grinding machine operatives
652 Lathe and milling machine operatives
653 Precision machine operatives, not elsewhere classified
656 Punch and stamping press operatives
660 Riveters and fasteners
661 Sailors and deckhands
662 Sawyers
663 Sewers and stitchers
664 Shoemaking machine operatives
665 Solderers
666 Stationary firemen

Textile operatives
670 Carding, lapping, and combing operatives
671 Knitters, loopers, and toppers
672 Spinners, twisters, and winders

673 Weavers
674 Textile operatives, not elsewhere classified
680 Welders and flame-cutters
681 Winding operatives, not elsewhere classified
690 Machine operatives, miscellaneous specified
692 Machine operatives, not specified
694 Miscellaneous operatives
695 Not specified operatives

TRANSPORT EQUIPMENT OPERATIVES
701 Boatmen and canalmen
703 Bus drivers
704 Conductors and motormen, urban rail transit
705 Deliverymen and routemen
706 Fork lift and tow motor operatives
710 Motormen; mine, factory, logging camp, etc.
711 Parking attendants
712 Railroad brakemen
713 Railroad switchmen
714 Taxicab drivers and chauffeurs
715 Truck drivers

LABORERS, EXCEPT FARM
740 Animal caretakers, except farm
750 Carpenters' helpers
751 Construction laborers, except carpenters' helpers
752 Fishermen and oysterman
753 Freight and material handlers
754 Garbage collectors
755 Gardeners and groundskeepers, except farm
760 Longshoremen and stevedores
761 Lumbermen, raftsmen, and woodchoppers
762 Stock handlers
763 Teamsters
764 Vehicle washers and equipment cleaners
770 Warehousemen, not elsewhere classified
780 Miscellaneous laborers
785 Not specified laborers

FARMERS AND FARM MANAGERS
801 Farmers (owners and tenants)
802 Farm managers

FARM LABORERS AND FARM FOREMEN
821 Farm foremen
822 Farm laborers, wage workers
823 Farm laborers, unpaid family workers
824 Farm service laborers, self-employed

SERVICE WORKERS, EXCEPT PRIVATE HOUSEHOLD
Cleaning service workers
901 Chambermaids and maids, except private household
902 Cleaners and charwomen
903 Janitors and sextons

Food service workers
910 Bartenders
911 Busboys
912 Cooks, except private household
913 Dishwashers
914 Food counter and fountain workers
915 Waiters
916 Food service workers, not elsewhere classified, except private household

Health service workers
921 Dental assistants
922 Health aides, except nursing
923 Health trainees
924 Lay midwives
925 Nursing aides, orderlies, and attendants
926 Practical nurses

Personal service workers
931 Airline stewardesses
932 Attendants, recreation and amusement
933 Attendants, personal service, not elsewhere classified
934 Baggage porters and bellhops
935 Barbers
940 Boarding and lodging house keepers
941 Bootblacks
942 Child care workers, except private household
943 Elevator operators
944 Hairdressers and cosmetologists
945 Personal service apprentices
950 Housekeepers, except private household
952 School monitors
953 Ushers, recreation and amusement
954 Welfare service aides

Protective service workers
960 Crossing guards and bridge tenders
961 Firemen, fire protection
962 Guards and watchmen
963 Marshals and constables
964 Policemen and detectives
965 Sheriffs and bailiffs

PRIVATE HOUSEHOLD WORKERS
980 Child care workers, private household
981 Cooks, private household
982 Housekeepers, private household
983 Laundresses, private household
984 Maids and servants, private household

V Two-Digit Occupational Codes

PROFESSIONAL, TECHNICAL
AND KINDRED WORKERS (001-195)[30]

10. Physicians (medical + osteopathic), Dentists (062,065)
11. Other Medical and Paramedical: chiropractors, optometrists, pharmacists, veterinarians, nurses, therapists, healers, dieticians (except medical and dental technicians, see 16) (061,063,064,071-076)
12. Accountants and Auditors (001)
13. Teachers, Primary and Secondary Schools (including NA type) (141-145)
14. Teachers, College; Social Scientists; Librarians; Archivists (032-036,091-096,102-140)
15. Architects; Chemists; Engineers; Physical and Biological Scientists (002,006-023,042-054)
16. Technicians: Airplane pilots and navigators, designers, draftsmen, foresters and conservationists, embalmers, photographers, radio operators, surveyors, technicians (medical, dental, testing, n.e.c.) (003-005,025,055,080-085,150-173,183,191)
17. Public Advisors: Clergymen, editors and reporters, farm and home management advisors, personnel and labor relations workers, public relations persons, publicity workers, religious, social and welfare workers (024,026,056,086,090,100-101,184,192)
18. Judges; Lawyers (030,031)
19. Professional, technical and kindred workers not listed above (174,175-182,185,190,193-195)

MANAGERS, OFFICIALS AND PROPRIETORS (EXCEPT FARM) (201-245)

20. Not self-employed
31. Self-employed (unincorporated businesses)

CLERICAL AND KINDRED WORKERS

40. Secretaries, stenographers, typists (370-372,376,391)
41. Other Clerical Workers: agents (n.e.c.) library assistants and attendants, bank tellers, cashiers, bill collectors, ticket, station and express agents, etc., receptionists (301-364,374-375,381-390, 392-395)

SALES WORKERS

45. Retail store salesmen and sales clerks, newsboys, hucksters, peddlers, traveling salesmen, advertising agents and sales- men, insurance agents, brokers, and salesmen, etc. (260-285)

CRAFTSMEN, FOREMEN,
AND KINDRED WORKERS

50. Foremen, n.e.c. (441)
51. Other craftsmen and kindred workers (401-440,442-580)
52. Government protective service workers: firemen, police, marshals, and constables (960-965)

OPERATIVES AND KINDRED WORKERS

61. Transport equipment operatives (701-715)
62. Operatives, except transport (601-695)

LABORERS

70. Unskilled laborers–nonfarm (740-785)
71. Farm laborers and foremen (821-824)

SERVICE WORKERS

73. Private household workers (980-984)
75. Other service workers: barbers, beauticians, manicurists, bartenders, boarding and lodging housekeepers, counter and fountain workers, housekeepers and stewards, waiters, cooks, midwives, practical nurses, babysitters, attendants in physicians' and dentists' offices (901-965 except 960-965 when work for local, state, or federal government)

FARMERS AND FARM MANAGERS

80. Farmers (owners and tenants) and managers (except code 71) (801-802)

MISCELLANEOUS GROUPS

55. Members of armed forces
99. NA; DK
00. Inap.; No to C42; unemployed; retired, permanently disabled, housewife, student; V7706=3-8; V7744=5 or 9

[30] Numbers in parentheses represent the 3-digit codes from the 1970 Census of Population.

VI One-Digit Occupational Codes

01. Professional, technical, and kindred workers (10-19)[31]
02. Managers, officials, and proprietors (20)
03. Self-employed businessmen (31)
04. Clerical and sales workers (40-45)
05. Craftsmen, foremen, and kindred workers (50-52)
06. Operatives and kindred workers (61-62)
07. Laborers and service workers, farm laborers (70-75)
08. Farmers and farm managers (80)
09. Miscellaneous (armed services, protective workers) (55)

[31] Numbers in parentheses represent 2-digit occupation codes, recoded by the authors based on PSID documentation.