Occupational Mobility and Wage Inequality*

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Abstract

In this article 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 the 1990s. The theory is also quantitatively consistent with the level and increase in the short-term variability of earnings.

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1 Introduction

Despite an active search for the reasons behind the large increase in (within-group) 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 within-group 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 mid 1990s. (1) Inequality of hourly wages has increased over the period − the variance of logs has increased from 0.225 to 0.354, or 57%, while the Gini coefficient has increased from 0.258 to 0.346, or 34%. (2) Most 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 throughout the entire wage distribution. (4) Individual earnings became substantially more volatile.

In Kambourov and Manovskii (2008) we document that there was a considerable increase in the fraction of workers switching occupations (e.g., cook, accountant, chemical engineer) over the same period. We find that the annual rate of occupational mobility in the U.S. has increased from 16% in the early 1970s to 21% in the mid 1990s. In addition, in Kambourov and Manovskii (2009) we find substantial returns to tenure in an occupation − an increase in wages of at least 12% after 5 years of occupational experience, holding other observables constant. This finding is consistent with the results from other studies discussed in Section 2.2 which, using different methodologies and data from different countries, provide evidence consistent with the occupational specificity of human capital and with the importance of the occupational search process.

Occupational mobility and wage inequality are interrelated because occupational mobility affects the distribution of occupational tenure and, thus, of human capital. In addition, occupations are characterized by fluctuating levels of productivity and demand for their services. Occupation-specific human capital ties people to their occupations and makes switching them difficult. Thus, the cross-sectional wage dispersion depends, among other things, on the distribution of occupational tenure in the population, and on the distribution of workers across occupations with different productivities and demands. 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 frameworks of Lucas and Prescott (1974) and Alvarez and Veracierto (2000). In these models 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. We build on the random search environment in Alvarez and Veracierto (2000) but instead of adopting this spatial interpretation we think of "islands" as occupations. Further, we introduce worker heterogeneity 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 human capital. Then, given that she remains in that occupation, her level of human capital increases over time. When an individual switches her occupation, she loses the specific human capital 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 mid 1990s.[1]

We quantify the effects of the increased variability of occupational productivity shocks in the following experiment. We calibrate the parameters of the model to match a number of

[1]The focus of this paper is quantitative. A theoretical analysis of various properties of the Lucas and Prescott (1974) equilibrium search model with undirected search (e.g., establishing a version of welfare theorems and characterizing efficient allocations) is developed in a series of papers by Alvarez and Veracierto (1999, 2000, 2005).

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 mid 1990s. At no point in the calibration do we target wage inequality.

Two important results emerge from our analysis. The first result is that even though wage inequality is not targeted, the model, calibrated to match the facts on occupational mobility, generates wage inequality and wage instability similar to the within-group measures in the data. For example, the variance of log wages in the model is around 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. We show that the presence of occupation-specific human capital is of central importance for the model's ability to generate substantial levels of wage dispersion − a version of the model without occupation-specific human capital, calibrated to the facts on occupational mobility, generates only a small amount of wage dispersion. The second major result is that the model captures almost all of the increase in within-group wage inequality and the increase in the short-term volatility of log earnings.

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 the 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 the observable increase in occupational mobility is one possible manifestation of the increased turbulence. We identify this part of 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)) or in the experience premium (e.g., Jeong, Kim, and Manovskii (2008)). The increase in the college or experience premia, however, each account for less than 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 the 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. Section 8 concludes. We discuss some of our modeling choices, some more features of the data, and the computational algorithm in the Appendices.

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.[2] 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

[2]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 (2004a, 2008, 2009).

analysis and are discussed when relevant.

The Concept of Wages. Let w_{it} denote real hourly earnings of individual i in year t obtained by the PSID by dividing real annual earnings by total hours worked. We refer to this measure of wages as *Overall*. We also define two additional measures of wages that better correspond to the notion of wages in the model developed below.

1. First, age and education have some effects on wages that are not present in the model. Consequently, we proceed to define wages net of the effect of these two variables. Following the standard approach in the literature (e.g., Katz and Autor (1999)), 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.[3] 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

[3] As in 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.

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 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:

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

where X_{it} contains the same variables as in (1) while Z_{it} contains a set of dummy variables for three-digit occupations and the tenure of individual i in his three-digit occupation.[4] Then, using the estimates $\hat{\theta}$ from regression 2, we define the *Within-Group 2* measure of residual (log) wages as:

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

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 to describe 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 individual 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. Thus, at least until the

[4] We drop each year all observations which belong to a three-digit occupation that has less than 7 observations in that year.

mid to late 1970s the occupational tenure measures are imprecise.[5]

Second, the three-digit occupational dummies are noisy, especially in the 1981-1997 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 genuine occupational affiliations. For example, if we 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 (2008, 2009), 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 *titles* 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 weighted 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 weight 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 the Online Appendix I.

[5]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.

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.[6] 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 the log 90/10 ratio, are similar.

In Figure 4 we plot the percentage change in real wages by percentiles of the wage distribution. The figure reveals that the increase in wage inequality between the early 1970s and mid 1990s reflects changes that affected all parts of the wage distribution. These findings are similar to those reported in Gottschalk (1997) and Topel (1997).[7]

2.1.2 Decline in Wage Stability

Following Gottschalk and Moffitt (1994), one can decompose the log annual earnings y_{it} of individual i in year $t = 1, 2, ..., T$ as:

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

[6] 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.

[7] While we have data only on individual wages, a more relevant concept for our analysis might be that of total compensation. Using 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.

where π_i is the mean log earnings of individual i over T years, while η_{it} is the deviation of y_{it} from the individual mean log earnings 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 and the second periods. These results imply that workers faced considerably higher wage variability in the 1990s than in the 1970s.[8, 9]

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 mid 1990s, at the three-digit level (see Online Appendices III - V 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.[10] The three-digit classification defines more than 400 occupations: architect, carpenter, and mining engineer are a few examples. Figure 6 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) found no trend in occupational mobility in the 1960s.[11]

[8]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, for instance, Moffitt and Gottschalk (1995) and Heathcote, Storesletten, and Violante (2004).

[9]The variance of the permanent component of wages has also increased over the period. The theory developed in this paper abstracts from any permanent individual heterogeneity, and as a result we do not study this aspect of the data.

[10]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.

In Kambourov and Manovskii (2008) we also show that computing mobility on a sample restricted only to workers who are employed both in the current year and in the previous year, would result in a level and an increase of occupational mobility that are both slightly lower than under our preferred measure of mobility. Calibrating the model to this measure of mobility would not change any of the conclusions in this paper.

[11]Parrado, Caner, and Wolff (2007) also argue in favor of an increase in occupational mobility in the United States from the late 1960s till the early 1990s. 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 1979-1997 period.

Several additional results from Kambourov and Manovskii (2008) 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. 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 (2009) 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, holding other observables constant. This finding is consistent with a substantial fraction of workers' human capital being occupation-specific and is supported by a large and growing body of literature. 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. Zangelidis (2007), finds large returns to occupational tenure in British data. 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. Since the results in these and numerous other papers imply large returns to occupational tenure, 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 and a measure one of ex-ante identical individuals. 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.[12] 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 occu-

[12] 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. 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.

pation 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

$$\ln(z') = \alpha(1-\phi) + \phi \ln(z) + \epsilon', \tag{5}$$

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).[13]

[13] 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. Kambourov (2009) studies the effect of labor market regulations on the sectoral reallocation of workers after a trade reform and solves for the full transition path toward the post-reform steady state.

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.[14] 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

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

If the 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, taking into account the fact that with probability p she will become experienced next period and with probability δ she will die.

[14]Since workers in the model have a choice of whether to stay in their occupation or leave, we find it reasonable and convenient 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.

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.[15] 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 $V_2(\psi, z) \geq V^s$.

[15] Our definition of equilibrium is similar to the one in Alvarez and Veracierto (2000) extended to include accumulation of specific human capital.

(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:

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

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 Online Appendix II.[16]

[16] Given the postulated production function, in general, one cannot guarantee uniqueness of the candidate policy $g(\psi, z)$ consistent with equilibrium (as would be the case if experienced and inexperienced workers were perfectly substitutable). Given our estimates below, experienced and inexperienced workers are only mildly complimentary, and thus we do not encounter such multiplicity (anywhere in the state space) when computing the model. As a precaution, however, our computational algorithm allows for such multiplicity. In particular, if there existed multiple candidate policies $g(\psi, z)$ consistent with equilibrium, it would select one that maximizes the value function

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

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

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 1969-96 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

We choose the model period to be two months. We think that the economically relevant choice of the model period is considerably longer. We chose such a short model period to emphasize that the model generates substantial wages dispersion for no other reason but the presence of occupation-specific human capital. In Kambourov and Manovskii (2004b) we present the results for the model calibrated with the model period of six months.

Because we assume that individuals forgo a period of earnings while switching occupations, the length of the model period represents the cost of switching occupations in addition to the amount of lost occupation-specific skills. Part of these costs comes from the costs associated with basic training necessary for entry into most occupations. It is difficult to measure the cost of such training directly. Heckman, LaLonde, and Smith (1999) report that the average vocational training program in the US takes about three months of study and has a direct cost of \$2,000 to \$3,000 in 1997 U.S. dollars. This monetary cost alone is close to two months of wages for the median worker in 1997. Thus, setting the costs of switching occupations to two months of forgone earnings appears quite conservative. Especially, given the fact that we assume risk-neutrality $-$ an assumption that further decreases the cost of switching occupations in the model.[17]

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 corresponds to an annual interest rate of 4%.

An investigation of the estimated returns to occupational tenure in Kambourov and Manovskii (2009) 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 explore 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

[17] In equilibrium, the workers who switch occupations on average find an acceptable new occupation in 9.4 weeks in the 1970s and 10.3 weeks in the 1990s.

wages paid to the experienced and inexperienced workers in an occupation (defined by the choice of p), 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 are then estimated with the OLS, 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 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 − which we also refer to as mobility persistence − is equal to 1.54 over the 1970-73 period and 1.71 over the 1993-96 period.[18]

[18] 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. 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.

Next, we choose ϕ and σ_ϵ to match the corresponding observations for the 1993-96 period. In Kambourov and Manovskii (2004b) we have shown that ϕ and σ_ϵ are uniquely identified by these two targets. 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.[19]

Table 4 summarizes the values of the parameters assumed to be fixed in both periods. Table 5 contains the values of α, ϕ, and σ_ϵ with which the model exactly matches the calibration targets in both periods (see Table 6). The values of the shocks and the stationary distributions of occupations over shocks in both periods can be found in Table 7.

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 8 reports the level of wage inequality and wage stability in the model and in the data for the 1970-1973 period.[20] The results indicate that the model generates wage inequality and wage instability similar to those in the data. For example, the variance of log wages in the model is around 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

[19]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. We discuss alternative normalizations below in Section 7.2.2.

[20]While the discussion in this section focuses on the performance of the model calibrated to the early 1970s, we would reach the same conclusions if we were to discuss the performance of the model calibrated to the mid 1990s.

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 9, 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 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. As seen in Table 12, 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 calibrate the model without occupation-specific human capital to match the same targets as in the benchmark calibration (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). We find that in the model without human capital 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 a 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.[21]

There are several channels that account for the importance of occupation-specific human capital in generating substantial wage inequality.

First, 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.

Second, 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.

Third, 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

[21] The results in this paper are not directly comparable to those in Hornstein, Krusell, and Violante (2006). They argue that search frictions in looking for *jobs* do not give rise to sizable wage dispersion in reasonably calibrated job search models. We, however, do not model employment relationships or unemployment. Thus, our model is silent on the value of leisure of unemployed workers − the key variable determining wage dispersion in a search model. Workers in our model can switch employers within an occupation at no cost at all. In this sense one may argue that for a worker in an occupation his flow utility of unemployment is close to his wage (as found in Hagedorn and Manovskii (2008)). Moreover, even for those who switch occupations, the flow utility of leisure/non-market activity may be quite high. However, the workers who decide to switch occupations have to pay the retraining cost. We assume that this cost is equal to the monetary expenditures on retraining and does not include the possibly high value of forgone leisure.

wages in the future.[22]

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 1969-1996 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.

7.1 Results

The results, summarized in Table 11, 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. To look deeper at the increase in wage inequality, we use the calibrated model to construct a graph of the relative change in wages by percentiles of the wage distribution. Figure 7 plots this change in the model and in the data.[23] The figure illustrates that the model does an excellent job matching the observation that the increase in within-group wage inequality in the data reflected changes that affected all parts of the wage distribution.

Inspecting the results in Table 12 from the re-calibrations of the model with different

[22]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.

[23]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. Figure 4 and Figure A-4 in the Online Appendix show the corresponding graphs for the other measures of wages and the actual population structure.

choices of p, one finds that 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.

7.2 Economics of the Results

In this section we discuss the economics behind the ability of the model to generate increases in occupational mobility and wage inequality similar to the data.

7.2.1 The Role of the Variance and Persistence of the Shocks

To clarify the role played by changes in the variance and persistence of the shock process we first consider the experiments of changing these parameters one by one in our benchmark calibration. The results are summarized in Table 10. Consider first the effects of changing the variance of the shocks. In terms of the discretized shock process, an increase in the variance of the shocks spreads the support of the shocks while leaving the transition probabilities and the stationary distribution of the shocks unchanged. This results in higher occupational mobility and higher wage inequality. The endogenous workers' mobility decisions tend to counteract the response of inequality to the increased dispersion of the shocks because the higher dispersion of the shocks induces more workers to leave unproductive occupations and search for more productive ones. However, the direct effect of higher dispersion of the shock values dominates.

A decline in the persistence of the shocks lowers occupational mobility and wage inequality. In terms of the discretized shock process it squeezes the support of the shocks, changes the transition probabilities significantly, and changes the stationary distribution of the shocks by putting less mass in the tails and more mass in the middle. The endogenous workers' mobility decisions tend to counteract the response of inequality to the decreased dispersion of the shocks because the lower dispersion of the shocks induces fewer workers to leave unproductive occupations and search for more productive ones. Moreover, the payoff from search declines because highly productive occupations are not expected to maintain their productivity advantage for as long as before, making the search for them (at the cost of forgoing human capital accumulation elsewhere) less attractive. However, as in the case of variance, the direct effect of lower dispersion of the shock values dominates.

Thus, a higher variance or a higher persistence could each generate the increase in occupational mobility and wage inequality. However, in our quantitative experiment both the variance and the persistence of the shock process change (the identification is achieved through the behavior of the second target – the persistence in mobility – which changes at different rates in response to changes in the variance and persistence). At the calibrated values, the net result is that between the 1970s and 1990s the support of the shocks increases (variance has a quantitatively bigger effect on this than persistence), the transition probabilities change in the direction that it becomes less likely to observe the same shock next period (the persistence effect dominates by far), and the stationary distribution of the shocks changes in the direction that there is less mass in the tails and more mass in the middle (again, the persistence effect dominates).

It turns out that the distribution of workers over the shocks (i.e., the fraction of workers on the lowest shock, second lowest, and so on to the highest shock) is very similar in the 1970s and 1990s. Given that the actual values of these shocks are different and more dispersed in the latter period, as can be seen in Table 7, wage inequality clearly increases. This is an interesting equilibrium outcome since (i) the new distribution of workers over the shocks is an equilibrium object, and (ii) even though this distribution is similar in the two periods, the actual patterns of mobility of workers in the model across occupations (and across productivity shocks) are quite different.

Consider, for example, an occupation which goes from being on shock 8 to shock 4 and consider what would happen to the workers in such an occupation in the 1970s and in the 1990s. Typically, some workers leave an occupation whose productivity declines. However, in the more volatile environment of the 1990s relatively more workers choose to remain in such an occupation. In other words, the marginal worker who leaves the occupation in the 1970s would choose to remain in that occupation in the 1990s. The reason for this is that in the more turbulent 1990s the gains of locating a productive occupations are higher but shorter lived and more people choose to preserve their human capital rather than taking a chance of building it in some temporarily more productive occupation.

This effect tends to reduce mobility and increase inequality. The decline in mobility is more than offset, however, by the fact that such transitions of occupations from, say, shock 8 to shock 4 occur considerably more often in the 1990s. The net effect is that more workers are "displaced" at the same time as some workers who would have left a relatively unproductive occupation in the tranquil 1970s choose to remain in it in the 1990s.

7.2.2 Alternative Normalizations of the Shock Process

We normalized the unconditional mean of the shock process, α, to be equal to zero in the first period and adjusted it in the second period to keep real average wages constant. 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. However, there is something to be learned from alternative normalizations. In particular, it would be interesting to measure the effect on the average wage of the larger aggregate loss of specific human capital caused by the increase in occupational mobility. It appears hard to cleanly isolate this effect, however.

Consider the following experiment. After calibrating the steady state describing the 1970s, we change the variance and persistence of shock process to match the targets on occupational mobility in the 1990s, but scale α down in order to have the average value of the shock z constant in the two periods (the average value of z, $\overline{z}$, is computed as $\overline{z} = \sum_i z_i f(z_i)$), where $f(z_i)$ is the stationary distribution of the shocks). Performing this experiment we find that average wages increase by approximately 3%. The reason is as follows. By going from the first to the second steady state, the support of the productivity shocks spreads out − the values of the shocks at the lower end of the shock distribution decrease and the values of the shocks at the upper end of the distribution increase. However, there are disproportionally less workers in the unproductive (low shock) occupations and a larger fraction of them in occupations with high productivity. As a result, by decreasing the value of the low shocks we are not affecting average wages significantly since this change affects only a small mass of workers. By increasing the values of the high shocks, however, we are increasing average wages since there is a substantially higher mass of workers there.

There are other channels which affect average wages in this experiment. First, the fact that there are more inexperienced workers in the 1990s decreases average wages. Second, due to the presence of the fixed factor in production, average wages would be slightly higher in the 1990s since there are more workers searching (and, therefore, less workers employed). Finally, a change in the distribution of workers (and also a change in the distribution of inexperienced and experience workers) over shocks also affects average wages. In the end it turns out that when we keep the average z constant the channels that increase the average wage dominate quantitatively the channels that decrease the average wage.[24]

As an alternative, consider the experiment of keeping the average z constant but using the distribution of workers over the shocks when computing it instead of the stationary distribution of shocks. In other words, we are keeping constant the average z for a worker taking into account the change in the distribution of workers over shocks. In this case the average wage falls by 1%. All of the additional three channels described above are at play in this experiment as well: there are more inexperienced workers (decreasing average wages),

[24]The effect that average wages increase with the variance of the shocks is reminiscent of the result that with complete markets and endogenous labor supply an increase in inequality increases the average productivity (see Heathcote, Storesletten, and Violante (2007)).

there are less employed workers (increasing average wages), the distribution of workers (and the distribution of inexperienced and experience workers) over shocks also changing slightly.

Thus, it is not entirely obvious what experiment should be conducted in order to isolate the effect of human capital only. Even though it seems that the effect of less human capital in the economy decreases average wages, its precise quantitative impact is not easily measurable.

7.3 Inequality Within and Across Occupations

In the calibrated model the increase in the variability of occupational productivity shocks results in a sizable increase in the dispersion of wages across occupations with a smaller increase of wage dispersion within occupations. We now contrast this implication of the model with the data. In Table 13 we summarize the variance of log wages between and within three-digit occupations in the 1970-1973 and 1993-1996 periods.[25]

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 occupations from 0.067 to 0.141 and an increase in the inequality within occupations from 0.109 to 0.140.

Recall that *titles* of occupations are noisy in the PSID, especially in the 1981-1996 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 titles in the 1990s, when only the originally coded data are

[25] We define between-occupation wage inequality as the variance of the mean of log wages in an occupation while within-occupation inequality is defined as the average (across all occupations) variance of log wages within an occupation.

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. 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 observed in the data. In addition, we have abstracted from any ex ante heterogeneity.[26]

7.4 Properties of the Shock Process

Evaluating what caused the increase in the variability of occupational shocks is 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 decline in the 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 or 40 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 of the occupational shocks. It could also decrease the persistence of these shocks − the relative productivity of an occupation might increase in response to a technological change today, but decline in response to another change tomorrow.[27]

2. Opening the economy to international trade makes occupations more exposed to shocks

[26] We have also abstracted from idiosyncratic shocks to individuals, firms and industries. Introducing such shocks may help account for the level of within-occupation inequality.

[27] 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.

than before. Changes in foreign demand or productivity changes in particular sectors in foreign countries have an impact on corresponding sectors in the domestic economy and, as a result, affect a certain set of occupations. Since sectoral changes in the rest of the world might hurt a particular domestic occupation in the current period while increasing its relative importance in the near future, a possible net outcome is an increase in the variance of the occupational shocks and a decline in their persistence.

3. Other mechanisms may also play a role. Labor unions that span several occupations may insulate workers from short-term fluctuations in demands for the services of particular occupations. De-unionization exposes workers to those shocks. Similarly, most firms employ 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.

In the data, similar to the model, we find that the persistence of log average wages in an occupation declined from the 1970s to the 1990s while the standard deviation of the innovations to occupational average wages increased. This finding is suggestive of an increase in the variance and decline in the persistence of the occupational productivities. Unfortunately, due to data limitations, we cannot directly estimate the change in the shock process 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. However, as discussed in Section 2, until the mid to late 1970s the occupational tenure measures are imprecise, and the three-digit occupational dummies are noisy, more so in the 1981-1996 period. Thus, it does not appear possible to reliably infer from the data the changes in the shock process.[28] Instead, we use the model and our calibration strategy to infer how the shock structure must have changed in order to match the change in occupational mobility, which we can measure precisely.

8 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 model, calibrated to match the facts on occupational mobility, exhibits levels of wage inequality and wage stability that are close to the within-group measures in the data. We show that the presence of occupation-specific human capital is of central importance for the model's ability to generate substantial levels of wage dispersion − a version of the model without occupation-specific human capital generates only a small amount of wage dispersion. Further, we find that the model, calibrated to match the observed 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.

The increase in occupational mobility and wage inequality in the model was driven by the increase in the variability of productivity shocks to occupations. It is possible, however, that wage inequality might have increased because of an increase in the relative productivity

[28] 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.

of experienced workers. The analysis of the model's performance with respect to a in Table 9 helps evaluate the effect of such change. Suppose that 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 increase in the variance of logs (from 0.120 to 0.149) and the variance of transitory log wages (from 0.096 to 0.110). It would, however, have the strongly counterfactual prediction of a decline in occupational mobility from 0.159 to 0.102. The reason is clear: if the returns to occupational experience increase, individuals respond by accumulating more human capital and switching their occupations less often.

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 possibility in Table 9 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 results in an increase in occupational mobility (from 0.159 to 0.211). It also implies, however, 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. 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.

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

Notes − 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

Notes – 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%

Notes – 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 (2008) for details.

Table 4: 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 5: 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 6: 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

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

Table 7: 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 8: 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 since several years are needed to properly identify permanent from transitory wages.

Table 9: Comparative Statics I, 1970-1973.

	Benchmark (1)	a=0.40 (2)	a=0.48 (3)	ρ=0.60 (4)	ρ=0.85 (5)	p=0.0133 (6)	p=0.0233 (7)	γ=0.56 (8)	γ=0.80 (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

Notes – 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 10: Comparative Statics II, 1970-1973.

	Benchmark (1)	ϕ=0.900 (2)	ϕ=0.936 (3)	ϕ=0.882 (4)	ϕ=0.954 (5)	σ_ϵ=0.14 (6)	σ_ϵ=0.22 (7)	σ_ϵ=0.10 (8)	σ_ϵ=0.26 (9)
Occupational mobility:									
	0.159	0.135	0.185	0.115	0.225	0.114	0.206	0.072	0.250
Mobility persistence:									
	1.540	1.488	1.558	1.431	1.582	1.409	1.627	1.259	1.681
Variance of log wages:									
	0.120	0.111	0.134	0.102	0.144	0.079	0.164	0.044	0.211
Log 90/10 ratio:									
	0.854	0.825	0.888	0.786	0.928	0.692	0.982	0.518	1.097
Gini coefficient:									
	0.198	0.190	0.212	0.181	0.223	0.161	0.233	0.120	0.265
Variance of transitory log wages:									
	0.096	0.086	0.109	0.078	0.128	0.062	0.137	0.033	0.185

Notes – Column (1) reports the statistics in the benchmark calibration of the model for the period 1970-73 in which $\phi = 0.918$ and $\sigma_\epsilon = 0.18$. 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 ϕ and σ_ϵ.

Table 11: 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

Note – In the data, the variance of transitory log wages is computed for the 1970-1978 and the 1988-1996 periods since several years are needed to properly identify permanent from transitory wages.

Table 12: 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

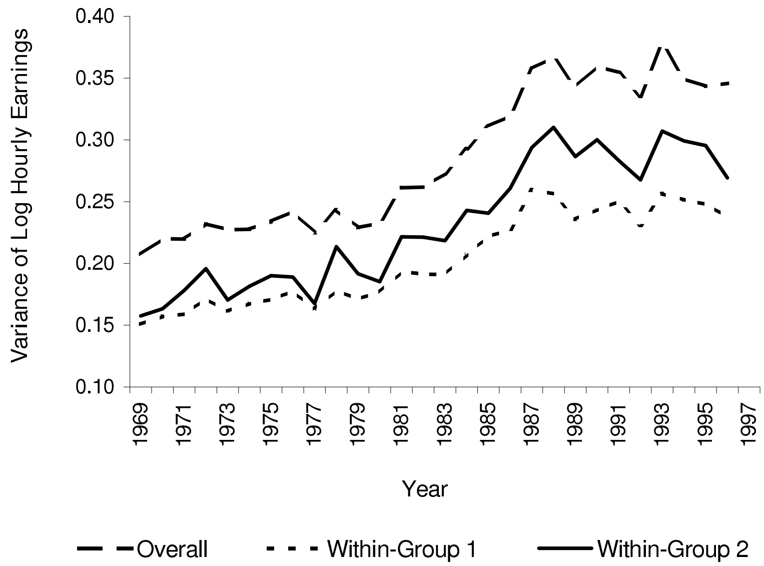
Notes – In the benchmark calibration of the model $p = 0.0167$, implying that it takes 10 years to become experienced in an occupation. This table reports the behavior of the model if the value of p is changed. In the first case, the value of p implies that it takes, on average, eight years to become 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, and then recalibrate the parameters governing the occupational shock process.

Table 13: 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

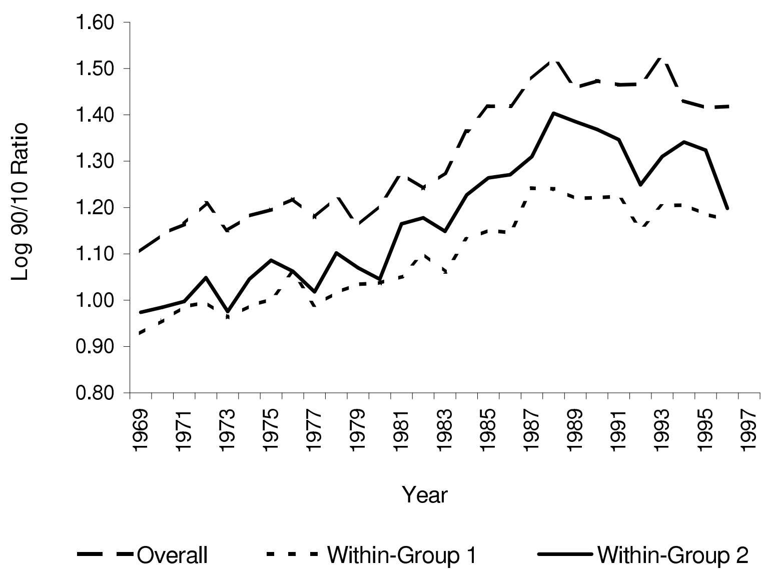
Notes − Between-occupation wage inequality is measured as the variance of the mean log wages in an occupation while within-occupation inequality is the average (across all occupations) variance of log wages within an occupation. We use the PSID and the sample is restricted to male household heads, aged 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, 1969-1996, PSID, Average Population Structure.



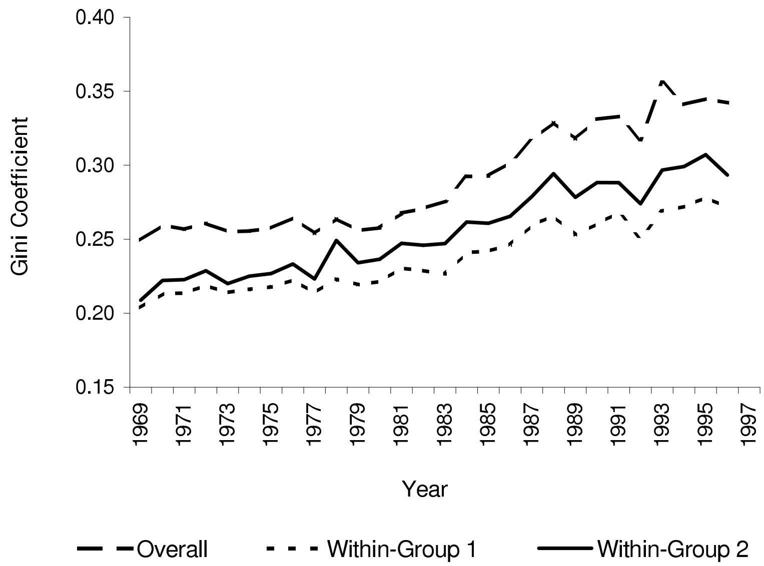
Source: Authors' calculations from the PSID.

Figure 2: Log 90/10 Ratio of Real Hourly Earnings in the United States, 1969-1996, PSID, Average Population Structure.



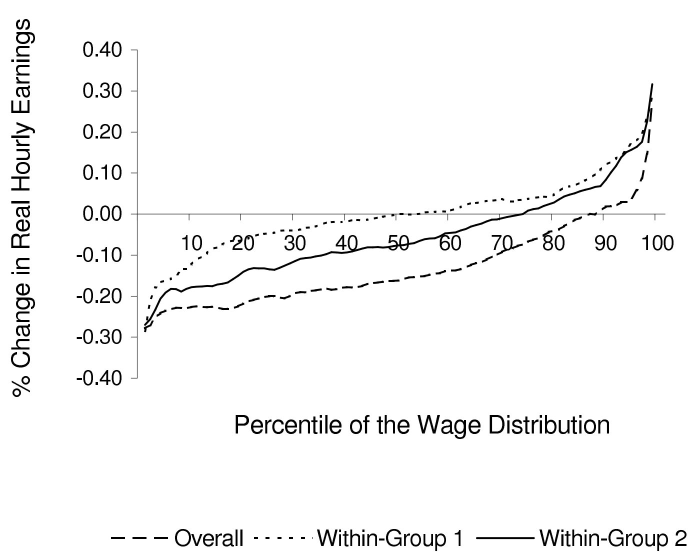
Source: Authors' calculations from the PSID.

Figure 3: Gini Coefficient of Real Hourly Earnings in the United States, 1969-1996, PSID, Average Population Structure.



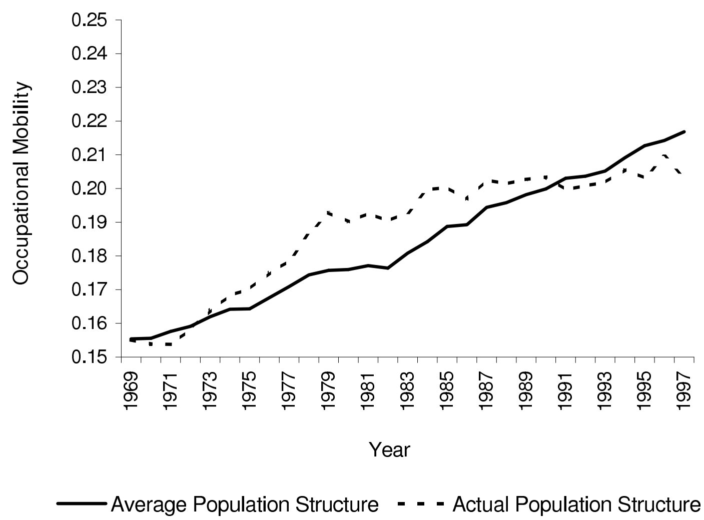
Source: Authors' calculations from the PSID.

Figure 4: Percentage Change in Real Hourly Earnings by Percentiles of the Distribution, 1993-96 vs. 1970-73, Average Population Structure.



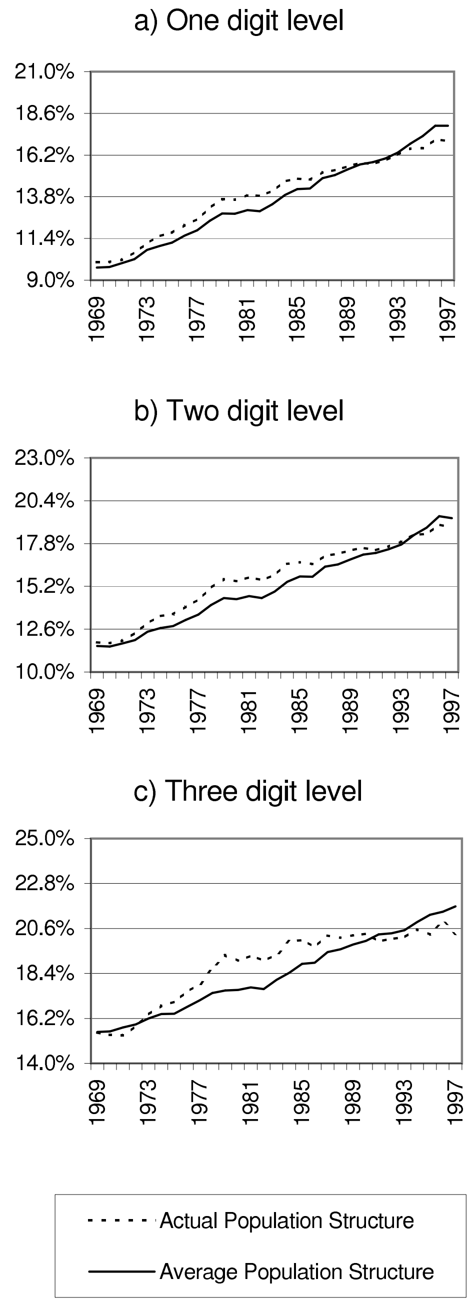
Source: Authors' calculations from the PSID.

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



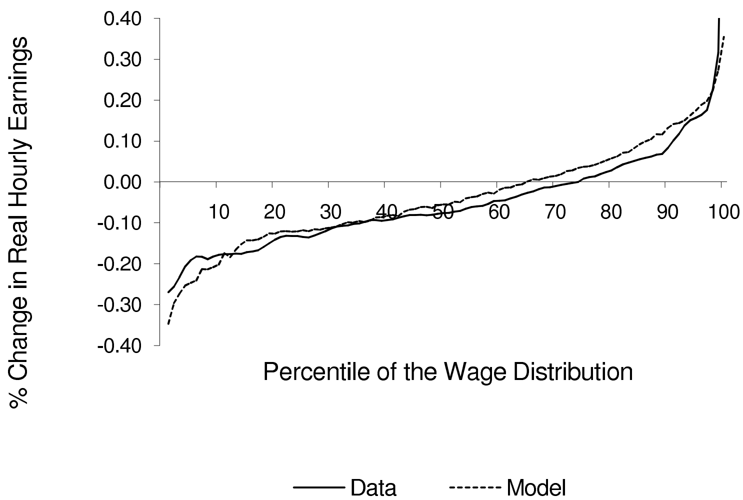
Source: Kambourov and Manovskii (2008).

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



Source: Kambourov and Manovskii (2008).

Figure 7: Percentage Change in Real Hourly Earnings by Percentiles of the Wage Distribution, 1993-96 vs. 1970-73, Model vs. Data.



Notes – 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 Figure A-4 in the Online Appendix show the corresponding graphs for the other measures of wages and the actual population structure.

References

ALVAREZ, F., AND M. VERACIERTO (1999): "Labor Market Policies in an Equilibrium Search Model," in *NBER Macroeconomics Annual*, ed. by B. Bernanke, and J. Rotemberg. The MIT Press.

——— (2000): "Equilibrium Search and Labor Market Policies: a Theoretical Analysis," mimeo, University of Chicago.

——— (2005): "Fixed Term Employment Contracts in an Equilibrium Search Model," Working Papers No. 14, Federal Reserve Bank of Chicago.

BERTOLA, G., AND A. ICHINO (1995): "Wage Inequality and Unemployment: United States vs. Europe," in *NBER Macroeconomics Annual*, ed. by B. Bernanke, and J. Rotemberg. The MIT Press.

BRAINARD, S. L., AND D. M. CUTLER (1993): "Sectoral Shifts and Cyclical Unemployment Reconsidered," *Quarterly Journal of Economics*, 108(1), 219–243.

CASELLI, F. (1999): "Technological Revolutions," *American Economic Review*, 89(1), 78–102.

GALOR, O., AND O. MOAV (2000): "Ability-Based Technological Transition, Wage Inequality, and Economic Growth," *Quarterly Journal of Economics*, 115(2), 469–497.

GOTTSCHALK, P. (1997): "Inequality, Income Growth, and Mobility: The Basic Facts," *Journal of Economic Perspectives*, 11(2), 21–40.

GOTTSCHALK, P., AND R. MOFFITT (1994): "The Growth of Earnings Instability in the U.S. Labor Market," *Brookings Papers on Economic Activity*, 2, 217–272.

Hagedorn, M., and I. Manovskii (2008): "The Cyclical Behavior of Equilibrium Unemployment and Vacancies Revisited," *American Economic Review*, 98(4).

Hamermesh, D. S. (1999): "Changing Inequality in Markets for Workplace Amenities," *Quarterly Journal of Economics*, 114(4), 1085–1123.

Heathcote, J., K. Storesletten, and G. L. Violante (2004): "The Macroeconomic Implications of Rising Wage Inequality in the United States," mimeo, New York University.

——— (2007): "Insurance and Opportunities: A Welfare Analysis of Labor Market Risk," *Journal of Monetary Economics*, forthcoming.

Heckman, J., R. LaLonde, and J. Smith (1999): "The Economics and Econometrics of Active Labor Market Programs," in *Handbook of Labor Economics*, ed. by O. Ashtenfelter, and D. Card, vol. 3A, pp. 1865–2097. Amsterdam: North Holland.

Hornstein, A., P. Krusell, and G. L. Violante (2006): "Frictional Wage Dispersion in Search Models: A Quantitative Assessment," Working Paper 06-7, Federal Reserve Bank of Richmond.

Jeong, H., Y. Kim, and I. Manovskii (2008): "The Price of Experience," mimeo, University of Pennsylvania.

Kambourov, G. (2009): "Labor Market Regulations and the Sectoral Reallocation of Workers: The Case of Trade Reforms," *Review of Economic Studies*, forthcoming.

Kambourov, G., and I. Manovskii (2004a): "A Cautionary Note on Using (March) CPS Data to Study Worker Mobility," mimeo, The University of Pennsylvania.

——— (2004b): "Occupational Mobility and Wage Inequality," PIER Working Paper No. 04-026; IZA Discussion Paper No. 1189.

——— (2008): "Rising Occupational and Industry Mobility in the United States: 1968-1997," *International Economic Review*, 49(1), 41–79.

——— (2009): "Occupational Specificity of Human Capital," *International Economic Review*, forthcoming.

Kambourov, G., I. Manovskii, and M. Plesca (2005): "Returns to Government Sponsored Training," mimeo, University of Pennsylvania.

Katz, L. F., and D. H. Autor (1999): "Changes in Wage Structure and Earnings Inequality," in *Handbook of Labor Economics*, ed. by O. Ashtenfelter, and D. Card, vol. 3A, pp. 1463–1555. Amsterdam: North Holland.

Krusell, P., L. E. Ohanian, J.-V. Ríos-Rull, and G. L. Violante (2000): "Capital-Skill Complementarity and Inequality: A Macroeconomic Analysis," *Econometrica*, 68, 1029–1053.

Kwon, I., and E. Meyersson Milgrom (2004): "Boundaries of Internal Labor Markets: The Relative Importance of Firms and Occupations," mimeo, Stanford University Graduate School of Business.

Ljungqvist, L., and T. J. Sargent (1998): "The European Unemployment Dilemma," *Journal of Political Economy*, 106(3), 514–550.

Lloyd-Ellis, H. (1999): "Endogenous Technological Change and Wage Inequality," *American Economic Review*, 89(1), 47–77.

Loungani, P., M. Rush, and W. Tave (1990): "Stock Market Dispersion, Unemployment, and GNP," *Journal of Monetary Economics*, 25(3), 367–388.

Lucas, R. J., and E. Prescott (1974): "Equilibrium Search and Unemployment," *Journal of Economic Theory*, 7, 188–209.

Manovskii, I. (2003): "Productivity Gains from Progressive Taxation of Labor Income," mimeo, University of Pennsylvania.

McCall, B. P. (1990): "Occupational Matching: A Test of Sorts," *Journal of Political Economy*, 98(1), 45–69.

Moffitt, R., and P. Gottschalk (1995): "Trends in Covariance Structure of Earnings in the U.S.: 1969-1987," mimeo, Boston College.

Moscarini, G., and K. Thomsson (2006): "Occupational and Job Mobility in the US," Discussion Paper 4.

Parrado, E., A. Caner, and E. N. Wolff (2007): "Occupational and Industrial Mobility in the United States," *Labour Economics*, 14(3), 435–455.

Pierce, B. (2001): "Compensation Inequality," *Quarterly Journal of Economics*, 116(4), 1493–1525.

Rosenfeld, C. (1979): "Occupational Mobility During 1977," *Monthly Labor Review*, 102(12), 44–48.

Shaw, K. (1984): "A Formulation of the Earnings Function Using the Concept of Occupational Investment," *Journal of Human Resources*, 14, 319–40.

——— (1987): "Occupational Change, Employer Change, and the Transferability of Skills," *Southern Economic Journal*, 53, 702–19.

Topel, R. H. (1997): "Factor Proportions and Relative Wages: The Supply-Side Determinants of Wage Inequality," *Journal of Economic Perspectives*, 11(2), 55–74.

Veracierto, M. (2002): "On the Cyclical Behavior of Employment, Unemployment and Labor Force Participation," Working Paper 2002-12, Federal Reserve Bank of Chicago.

Violante, G. L. (2002): "Technological Acceleration, Skill Transferability and the Rise in Residual Inequality," *Quarterly Journal of Economics*, 117(1), 297–338.

Zangelidis, A. (2007): "Occupational and Industry Specificity of Human Capital in the British Labour Market," *Scottish Journal of Political Economy*, forthcoming.

APPENDICES

I Discussion of Modeling Choices

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:

$$y = F(L, K, z) = zL^{\gamma}K^{\kappa}, \tag{A1}$$

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:

$$K = \left[\frac{r}{z\kappa}\right]^{\frac{1}{\kappa-1}} L^{\frac{\gamma}{1-\kappa}}. \tag{A2}$$

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

$$w_i(L, z; r) = a_i z^{\frac{1}{1-\kappa}} \gamma g_i^{\rho-1} \left[\frac{r}{\kappa}\right]^{\frac{\kappa}{\kappa-1}} L^{\frac{\gamma+\kappa\rho-\rho}{1-\kappa}}. \tag{A3}$$

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.

Productivity vs. Demand Fluctuations. We have modeled occupations as producing a homogeneous good and occupational shocks as shocks to the production function in an occupation. There is an isomorphic representation of occupations as producing different goods and shocks are to the 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. With these assumptions, 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 a high demand 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 restrictions 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 two 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 the present discounted value of lifetime earnings of inexperienced workers in the model. The 90 to 10 ratio is less than 1.03.

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.

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.