Accounting for the Changing Life-Cycle Profile of Earnings*

Gueorgui Kambourov†
University of Toronto

Iourii Manovskii‡
University of Pennsylvania

VERY PRELIMINARY AND INCOMPLETE

Abstract

We document a significant flattening of life-cycle earnings profiles for the successive cohorts of male workers entering the labor market since the late 1960s. Further, we provide evidence on the steepening in the profiles of earnings inequality and an upward shift in the profiles of occupational mobility for more recent cohorts. We develop a theory that relates these developments and study quantitatively what fraction of the change in the life-cycle profiles of earnings and earnings inequality is accounted for by the economic forces that drive the increase in occupational mobility. Preliminary results indicate that the increase in the variability of productivity shocks to occupations coupled with the increase in the rate of idiosyncratic destruction of occupational matches from the 1960s to the 1990s, may account for all these observations. The theory we propose is consistent with other facts characterizing the changes in the labor market, such as a sharp increase in cross-sectional wage inequality and the increase in the transitory variability of earnings.

JEL Classification: E20, E24, E25, J24, J31, J62.

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†Department of Economics, University of Toronto, 150 St. George St., Toronto, ON, M5S 3G7 Canada. E-mail: g.kambourov@utoronto.ca.

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

1 Introduction

Since the early 1970s the labor market in the United States has changed along several dimensions. One fact that has received substantial attention is the observed increase in the wage dispersion. Most of the literature accounting for this increase has focused on the college premium - i.e., the fact that the difference in wages of college and high school graduates has increased over the period. Others have argued that some of the increase is accounted for by an increase in the experience premium - i.e., the difference in wages of older and younger workers has increased over the period. Most of the increase in wage inequality, however, cannot be explained by an increase in the college and the experience premium. Indeed, Juhn, Murphy, and Pierce (1993) estimate that over half of the increase in the wage dispersion was due to rising wage inequality within age-education groups.

In this paper we present evidence that life-cycle earnings profiles have been flattening significantly for the successive cohorts of male workers entering the labor market since the late 1960s. In addition, we document that successive cohorts entering the labor market over the period are characterized by successively higher fractions of workers switching occupations (e.g., cook, accountant, chemical engineer) at all stages of their life-cycle. We evaluate quantitatively the relationship between occupational mobility and the life-cycle earnings profile and find that the increase in occupational mobility accounts for a substantial fraction of the life-cycle earnings profiles' flattening as well as the changes in the experience premium and the within-group inequality.

The new empirical finding on the flattening life-cycle profiles of wages and earnings that we introduce in this paper is important for understanding the changes in wage inequality and puts measurable restrictions on the candidate theories accounting for it. We will document that those who entered the labor market in, say, the 1990s faced similar entry-level real wages to those who entered it in the 1970s. More recent entrants, however, experience a significantly lower wage growth as they age. This evidence suggests that some of the facts on wage inequality so far have been misinterpreted. For example, the claim that the experience premium has increased was based on cross-sectional evidence showing that older workers in the 1990s are earning much more than younger ones as compared to the 1970s. This, however, cannot be interpreted as an increase in the returns to overall labor market experience. The evidence on life-cycle earnings profiles indicates that the relative pay of older workers is higher than a few decades earlier because young workers in the 1990s are on a lower life-cycle earnings profile as compared to earlier cohorts.[1]

The link between occupational mobility and life-cycle profiles is motivated by our finding in Kambourov and Manovskii (2008a) that human capital is specific to the occupation in which an individual works. We show that occupational experience is considerably more important in determining wages than either industry or employer tenure. This is intuitive: one would expect the human capital loss of a truck driver who loses a job in some food industry and finds another one in the furniture industry to be lower than the loss of a truck driver who becomes a cook. This motivated the analysis in Kambourov and Manovskii (2004b), where we argued that changes in occupational mobility over time are intimately related to changes in the wage dispersion within age-education groups. Since a sizable share of workers' human capital is generated by occupation-specific experience, a substantial fraction of the average life-cycle profile of wages can be explained by rising average occupational experience over the life-cycle of a cohort of workers who entered the labor market at the same time. An increase in occupational mobility results in lower average occupational experience over the cohort's life-cycle and a flatter life-cycle wage profile.

Occupational mobility, however, affects not only the distribution of occupational tenure and human capital. Different occupations are characterized at a point in time by different levels of demand or different productivity levels. Thus, in addition to the accumulation of occupational tenure, life-cycle earnings profiles and wage dispersion depend on the distri-

[1] We are not the first to suggest that there might be an important difference in cross-sectional and cohort based profiles. Some recent references include MaCurdy and Mroz (1995), Heckman, Lochner, and Todd (2003), and Heathcote, Storesletten, and Violante (2004b). To our knowledge, however, we are the first to rigorously document the flattening of life-cycle earnings profiles for males in the U.S. Related findings are reported in Bernhardt, Morris, Handcock, and Scott (1999) who find evidence of slower wage growth among workers younger than 36 across two NLSY cohorts of workers, and in Beaudry and Green (2000)) who document a similar pattern in the Canadian data. Welch (1979) and Berger (1985) were the first to provide a very early evidence on the flattening profiles at the time when Baby Boom generation was entering the labor market. They have interpreted the evidence as suggesting that larger cohorts have flatter earnings profiles. Our results suggest that slope of the profile has little relationship to cohort's size.

bution of workers across occupations at different points over the lifetime of the cohort. To evaluate the connection between occupational mobility, inequality, and life-cycle earnings profiles, we develop and quantitatively study an equilibrium model in which occupational mobility decisions are endogenously determined.

The model we develop is based on the substantially modified equilibrium search framework of Lucas and Prescott (1974). In that model, agents can move between spatially separated local labor markets that the authors refer to as "islands," and, although each local market is competitive, there are frictions in moving between locations. Here we do not adopt this spatial interpretation, but think of "islands" as occupations. As in Kambourov and Manovskii (2004b), we introduce a heterogeneity of workers with respect to their occupational experience levels and allow for occupation-specific as well as general human capital. Thus, when an individual enters an occupation, she has no occupation-specific experience. Then, given that she remains in that occupation, her level of experience changes over time. When an individual switches her occupation, she loses the experience accumulated in her previous occupation. The model contains a fairly rich age structure, that is required to quantitatively study life-cycle profiles. To our knowledge this paper is the first to embed life-cycle into a version of the Lucas and Prescott (1974) model. We reduce the dimensionality of the state space as compared to the original model by assuming a constant returns to scale production function in each occupation. Occupations are subject to idiosyncratic productivity shocks. We argue that the variability of these shocks has increased from the early 1970s to the early 1990s.

We quantify the effects of the increased variability of the occupational productivity shocks in the following experiment. We calibrate the parameters of the model to match a number of observations for the late 1960s. Next, we postulate that there was a gradual change in the environment over the 1970-2004 period and assume that the only parameters that were changing were the ones governing the variability of the productivity shocks to occupations and the rate of the idiosyncratic destruction of occupational matches. We calibrate the time paths of these parameters to match changes in occupational mobility over time. We *do not* target life-cycle profiles of earnings or earnings inequality over the transition. Given the time path of values of these four parameters we compute forward the transitional path of the economy for the cross-section of cohorts present in the market in 1970 and all the newly entering cohorts. We study the implications of these changes for the flattening of the life-cycle profiles of earnings, steepening of the life-cycle profiles of wage inequality, the dynamics of cross-sectional wage inequality over the transition, and the dynamics of wage stability over the transition.

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 Section 3. The calibration and the quantitative experiment we perform are detailed in Section 4. The results are described in Section 5. In Section 6, we discuss the modeling choices, investigate robustness, and evaluate possible alternative explanations for the rising occupational mobility and flattening life-cycle profiles. Section 7 concludes.

2 Facts

2.1 Changes in the Labor Market

Since the early 1970s, the US labor market underwent significant changes along several dimensions - life-cycle earnings profiles became flatter, 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 on male heads of households 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, and we need to follow individuals over time in some of our analysis. Second, the PSID is a unique data set that permits the construction of consistent measures of occupational mobility over the 1968-1997 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] For the analysis of changes in life-cycle profiles of earnings we also use the Current Population Survey (CPS) data over the 1963-2004 period. The CPS has the advantage of being a much larger data set, but it does not permit the study of the changes in occupational mobility for the reasons discussed in Kambourov and Manovskii (2004a).

We restrict the PSID sample to male heads of household, aged 18-61, who are not self- or dual-employed and who are not working for the government. The resulting sample consists of 65,187 observations over the 1968-1997 period, with an average of 2,172 observations a year. To the extent possible we impose similar restrictions on the CPS sample as well. Additional sample restrictions are imposed in some of the analysis and are discussed when relevant.

2.1.1 Changing Life-Cycle Profiles of Earnings

In this section we document that life-cycle earnings profiles in the United States have flattened over the 1960-1990 period for more recent cohorts. A cohort is denoted by the year in which individuals in that cohort turn 18 and enter the labor market. For instance, the 1968 cohort consists of individuals who were 18 in 1968. In order to study the behavior of life-cycle earnings profiles, we follow the average real annual earnings for the cohort from the time it enters the labor market at 18 years of age until it retires at the age of 64. Since our PSID data covers the period from 1968 till 1997, we observe only part of the life-cycle profiles for most of the cohorts. We restrict the analysis to full-time full-year workers. This restriction is not qualitatively important, but helps isolate changes in wages from changes in hours worked, and we do not have a good measure of hours in the CPS throughout the period.

Figure 1 presents a preliminary look at the data and the change in the earnings profiles over time. It plots, for a number of cohorts, the average real annual earnings over the life-cycle. We observe that the earnings profiles have changed over time - the earnings profile

[2] To deal with the measurement error problem, we develop a method based on the Retrospective Occupation-Industry Supplemental Data Files recently released by the PSID. 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 (2004b, 2008a,b).

of the 1988 cohort is quite different from those of the 1968 and 1978 cohorts. We do not observe any significant change in the average earnings at the time when the cohort enters the labor market. However, the pattern is suggesting that the life-cycle profiles for more recent cohorts have flattened.

In order to utilize the information contained in all the cohorts in our PSID and CPS samples and to study whether the flattening of life-cycle earnings profiles is statistically significant, we estimate the following regression model:

$$w_{it} = \beta_0 + \beta_1 z_i + \beta_2 z_i^2 + \beta_3 z_i * x_{it} + \beta_4 x_{it} + \beta_5 x_{it}^2 + \beta_6 x_{it}^3 + \epsilon_{it}, \tag{1}$$

where w_{it} is log average real annual earnings of cohort i in period t, x_{it} is the age of cohort i in period t, z_i is the entry year of cohort i, and ϵ_{it} is a white noise term.[3] The quadratic in the cohort entry year allows for different profile intercepts for the different cohorts. The cubic in age gives all cohorts a similar shape, while the interaction of the linear age and cohort terms allows different cohorts to have different slopes of the earnings profiles. For instance, if the coefficient on the interaction term is negative, then every successive cohort has a flatter earnings profile.

The resulting PSID earnings profiles, from the age of 18 till 46, are plotted on Figure 2. The figure reveals again that the labor market experience for recent cohorts has changed dramatically - while the entry average earnings are very similar, the cohorts entering the labor market in the late 1980s face a much flatter earnings life-cycle profile than the earlier cohorts. The estimation results from Equation 1 in the PSID data are summarized in Column (1) of Table 1. The coefficient on the interaction of the linear age and cohort terms is negative and statistically significant indicating that the flattening of the earnings profiles observed in the figure is statistically significant.

We conducted sensitivity analysis that confirms that this labor market change is quite pervasive and robust. The flattening is present if we also include in the sample government, self-employed and part-time workers. We also experimented with business cycle variables, such as real GDP growth or the unemployment rate, aimed at capturing the effect of booms

[3]A similar model was estimated on Canadian data by Beaudry and Green (2000). MaCurdy and Mroz (1995) discuss related specifications.

and recessions on earnings. They, however, have almost no effect on the results and are omitted from the analysis. We also investigated whether the results are robust to including an interaction of the linear cohort term and the higher order age terms and found that they were virtually not affected.

Next, we divided the sample into individuals with (1) a high-school degree and less and (2) some college and college. From Figure 3, which plots the earnings profiles for these separate groups, it is clear that recent cohorts of both educated and uneducated workers are faced with flatter earnings profiles. The flattening is considerably more pronounced for less educated workers. Note that higher-educated workers have steeper earnings profiles. This leads to a composition bias that works against our findings. The reason is that the fraction of educated workers was rising in more recent cohorts, that should have resulted in a steepening of the overall life-cycle earnings profiles.

Examination of the changes in life-cycle earnings profiles in the CPS reveals very similar patterns. Figure 4 graphs the earnings profiles from the raw CPS data. They are are very similar to the results we observed on the PSID data. Further, Figures 5 and 6, which report the earnings profiles (total and by education groups) smoothed by the procedure described in Equation 1, are almost identical to those on the PSID data. Column (1) of Table 2 shows that the flattening of the earnings profiles is statistically significant in the CPS data as well.[4]

[4]While we have data only on individual wages and earnings, a more relevant concept for our analysis is that of total compensation that also includes fringe benefits (e.g., employer provision of health and dental insurance, pension coverage, vacation pay, and training/educational benefits) and, perhaps, working conditions (e.g., shift work, irregular shifts, and workplace safety). Bosworth and Perry (1994), among others, report that total compensation grew faster than wages, especially in the 1970s. Is it likely that a slower wage growth for newer labor market entrants can be compensated by a faster growth in non-wage compensation? Unfortunately, it appears impossible to answer this question definitively because of the lack of relevant data. An indirect argument can be made, however. Using the establishment survey data for the 1981-1997 period, Pierce (2001) finds that non-wage compensation is strongly positively correlated with wages. This is not too surprising because, for example, employer contributions to pension plans and vacation pay are directly proportional to earnings. Employer spending on worker training are relatively small, but also proportional to workers' tenure, and, thus, wages. If one incorporates a measure of working conditions into the definition of total 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. This suggests that workplace amenities are also positively correlated with earnings. In this case, the growth in non-wage compensation can be interpreted as a special kind of time effects. Their presence may not affect the conclusion that life-cycle profiles of compensation have also flattened for more recent cohorts.The effect of the growth in non-wage compensation that is

Further sensitivity analysis.

1. McGrattan and Rogerson (2004) have documented a decline in hours worked by male workers in the US. Moreover, they found a reallocation of hours worked from older to younger workers. To minimize the impact of changes in hours worked we restricted the analysis to full-time full-year workers. To evaluate the extent to which changes in hours still affect our findings, we study the changes in the life-cycle profiles of hourly wages. This information is available only in the PSID throughout the period we study. The results, reported in column 5 of Table 1 and Figures 9 and 10, are in accord with the flattening profiles of the average annual earnings documented above.

2. The difficulty in simultaneously identifying cohort, time and age effects is well known. It lies in the fact that any two of these variables imply the third one. More formally, letting t denote the calendar year, we have $z = t - x$. Substituting this relation into Equation 1, we obtain (suppressing the subscripts):

$$w = \beta_0 + \beta_1 t + \beta_2 t^2 + (\beta_3 - 2\beta_2)t * x + (\beta_4 - \beta_1)x + (\beta_5 - \beta_2 - \beta_3)x^2 + \beta_6 x^3 + \epsilon. \qquad (2)$$

Thus, without additional restrictions, the statistical models summarized in Equations 1 and 2 are indistinguishable. We will not pursue any attempts to statistically distinguish between them. Instead, we will use the explicit economic model to account for the data.

Several aggregate time effects, however, may affect the inference from our specifications. First, it has been argued in the literature that various versions of the CPI and other indices have overstated the inflation rate in the 1970s. Second, there was a well documented slowdown of productivity growth in the US in the 1970s and 1980s. (Bosworth and Perry (1994) present evidence supporting both of these arguments.) To take a better account of these macroeconomic effects we estimate two additional versions of the model in Equation 1.[5] First, we incorporate a full set (except one) of year dummies into Equation 1. The results of this experiment are presented in Column 2 of Tables 1 and 2. Not surprisingly,

largely independent of wages, such as health insurance, is less clear.

[5] Note that our finding of a significant flattening of the profiles of log wages, implies more than a proportional decline in the productivity of the newer cohorts.

a finer account for the aggregate effects slightly improves the fit of the model. Flattening of the life-cycle profiles becomes even more pronounced.

Second, we note that, by definition, aggregate effects affect all workers in a given year in the same way. Thus, we can purge the data of these effects by dividing all wages in a given year by the wages of, say, newcomers into the market in that year. We estimate Equation 1 on the resulting data. The results are summarized in Column 3 of Tables 1 and 2. Again, we find a clear evidence of a flattening of the life-cycle earnings profiles.[6]

3. In our basic analysis we have defined cohorts based on the year in which members of the cohort turn 18. Since college educated workers enter the labor market later than the less educated workers, and the fraction of college educated workers changed over the period we analyze, this may potentially lead to important biases. Thus, it is insightful to examine whether the flattening persists if we define cohorts by the year in which its members enter the labor market. For instance, the 1968 cohort consists of all individuals who entered labor market in 1968. The results of estimating Equation 1 based on the year of labor market entry are presented in Column 4 of Tables 1 and 2 and Figures 7 and 8. These results are remarkably similar to our findings for age cohorts.

2.1.2 Increase in Occupational Mobility

As summarized in Figures 13 and 14 and Table 3, we find that occupational mobility in the U.S. has increased from 16.5% in the early 1970s to 20.5% in the late 1990s, at the three-digit level (see Appendices I - III 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.[7] The three-digit classification defines more than 400 occupations: architect, carpenter, and mining

[6] In order to allow for the macroeconomic effects to potentially affect differently workers from different education groups, we tried to divide the wages of all high school dropouts by the wages of high school dropouts entering the market in a given year, and similarly for all other education groups. We found the profiles flattening for all the subgroups.

[7] 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.

engineer are a few examples. In Kambourov and Manovskii (2008b) we show that even at the one-digit level - a classification that consists of only nine broad occupational groups - there was a substantial increase in occupational mobility. Rosenfeld (1979) suggests that occupational mobility did not exhibit any trend in the 1960s.

Figure 15 reveals the level of occupational mobility by cohorts. First, we observe that the level of occupational mobility declines as a cohort ages. Second, until the age of 50, workers in more recent cohorts switch occupations more often while for workers older than 50 there does not seem to exist a significant difference in occupational mobility across cohorts.

Several additional results detailed in Kambourov and Manovskii (2008b) are relevant to this study and will motivate our modeling choices. 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. The fact that, over the period, the population composition changed in favor of relatively less mobile older and more educated workers masked some of the increase in mobility. In fact the increase in the aggregate occupational mobility would have been 2 percentage points higher if the age-education structure of the population remained constant throughout the period. Second, mobility has increased in all parts of the occupational tenure distribution. Third, the increase in occupational mobility was not driven by an increased flow of workers into or out of a particular one-digit occupation. Thus, we find no evidence of an increase in stepping-stone mobility described in Jovanovic and Nyarko (1997). Fourth, as seen in Figure 16, we find a very similar increase in net occupational mobility defined as one-half of the sum of the absolute changes in occupational employment shares. That is, if $s_{m,t}$ is the fraction of employment in occupation m in year t, net mobility in year t is given by $1/2 \sum_m |s_{m,t} - s_{m,t-1}|$. Fifth, we note that occupational switches are fairly permanent: only around 20% of switchers return to their three-digit occupation within a four-year period.

We conclude that the high level of occupational mobility described here potentially implies a sizable yearly destruction of specific human capital. The increase in occupational mobility from the early 1970s to the early 1990s has significantly affected the labor market.

2.1.3 Increase in Wage Inequality

As Table 3 shows, the Gini coefficient of hourly wages for male workers has increased substantially from 0.26 in the early 1970s to 0.33 in the early 1990s. While some of the increase is due to the fact that the earnings premium for educated and experienced workers rose over the period, Juhn, Murphy, and Pierce (1993) estimate that over half of the increase in wage inequality was due to rising inequality within age-education groups. For example, as Figure 11 illustrates, wage inequality among college-educated workers and among high school-educated workers increased substantially during the period.

Figure 12, which is reproduced from Gottschalk (1997), reveals that the increase in wage inequality reflects changes that affected all parts of the wage distribution. The figure suggests that, between 1973 and 1994, real weekly wages have declined for almost 80% of American men and have increased only for the top 20%. These findings are similar to those reported in Topel (1997).[8]

2.1.4 Decline in Wage Stability

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

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

where π_i is the mean log wage of individual i over T years, while η_{it} is the deviation of y_{it} from the individual mean log wage in year t. Denote by $var(\eta_i)$ the variance of η_{it} for individual i over the T years. Following Gottschalk and Moffitt (1994), we compute the

[8] As mentioned above, while we have data only on individual wages, a more relevant concept for our analysis is that of total compensation. Using the establishment survey data for the 1981-1997 period, Pierce (2001) finds that 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.

variances of permanent and transitory components of log wages for the periods 1970-78 and 1979-87 on our sample, after first purging wages of age and education effects by regressing them on a quartic in age and a quadratic in education. Table 3 shows that the variance of permanent log wages, π_i, increased 29%, while the average (across individuals) variance of transitory wages, η_{it}, increased 56% over the period. These results imply that workers faced considerably higher wage variability in the 1980s than in the 1970s.[9]

2.2 Occupational Specificity of Human Capital

In Kambourov and Manovskii (2008a) we found substantial returns to tenure in a three-digit occupation - an increase in wages of at least 19% after 10 years of occupational experience. Table 4 summarizes the finding and the estimation procedure. Furthermore, we found that when experience in an occupation is taken into account, tenure within an industry or with an employer has virtually no effect on workers' wages. In other words, as long as a worker remains in the same occupation, her wages will keep growing regardless of whether she switches her industry or her employer. This finding is consistent with human capital being occupation-specific.

3 Model

Environment. The economy consists of a continuum of occupations of measure one and ex-ante identical individuals of measure one. Individuals live for J periods.

Preferences. Individuals are risk-neutral and maximize:

$$E \sum_{j=1}^{J} \beta^{j-1} w_j, \tag{3}$$

where β is the time-discount factor and w_j denotes individual earnings in j's period of life. The decision rules and equilibrium allocations in the model with risk-neutral workers are

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

equivalent to those in a model with risk-averse individuals and complete insurance markets.

Earnings Function. Earnings of a j-year old worker i are a function of human capital, $h_{i,j}$, and of the idiosyncratic productivity shock, z_i, to the occupation this worker is employed in:

$$w_{i,j} = z_i * h_{i,j}. \tag{4}$$

Occupational productivity shocks follow a Markov process characterized by the transition function $Q(z, \cdot)$. Realizations of z are independent across occupations. The Markov process for z is assumed to possess an invariant distribution ζ that satisfies $\zeta(Z) = \int Q(z, Z)\zeta(dz)$, where Z denotes sets of idiosyncratic productivity shocks.[10]

Human Capital Accumulation. Workers accumulate human capital with work experience through learning-by-doing. A fraction of workers' human capital is occupation-specific, and newcomers to an occupation, regardless of the experience they had in their previous occupations, begin as inexperienced workers. The remaining fraction of human capital is general, i.e. transferable across occupations. The lowest possible levels of general and specific human capital are normalized to 1. A worker of age j in the current period, has $G(j)$ units of general human capital. At the beginning of the following period she will possess $G(j + 1)$ units of general human capital. The law of motion for general human capital is

$$G(j + 1) = G(j)f_g(j) \tag{5}$$

A worker who has $o - 1$ periods of occupational experience this period will have o periods of occupational experience next period if he does not switch his occupation, and no occupational experience if he does. Occupational experience generates occupation-specific

[10]Since we are after characterizing a complete transition path of the model, which is an enormous computational task, we cast our exercise as a decision theoretic problem. As we illustrate in Section 6.2, the model is isomorphic to the one with capital and labor and constant returns to scale production in each occupation. A more general model that includes interactions across individuals through, say, decreasing returns, will have the (non-stationary over the transition) distribution of workers across age, human capital, and occupations as its state variable.

human capital according to the function $S(o)$ with the following law of motion:

$$S(o) = \begin{cases} S(o-1)f_s(o-1) & \text{if staying in the occupation,} \\ S(1) & \text{if switching to a new occupation.} \end{cases} \quad (6)$$

The total effective units of labor of a worker i who possesses G_i units of general human capital and S_i units of occupation-specific human capital are given by the aggregation $h_i = H(S_i, G_i)$.

Individual Decision Problem. Before entering the model workers observe current productivities in N_e occupations drawn independently across individuals from the invariant distribution ζ, pick the occupation with the highest productivity among them, and enter that occupation in the first period of their life iun the model. At the beginning of each period workers observe the current level of productivity, z_1, in their occupation and the current productivities of N other occupations. Outside offers are generated by independent draws across individuals and across time from the invariant distribution ζ. Let $z_2 \sim \xi = [\int_{-\infty}^{x} \zeta(x)dx]^N$ be the maximal of N offers. Based on these observations workers decide whether they prefer to remain in their current occupation or to switch to a new one at the beginning of the following period. Switchers find it better in expected terms to sacrifice specific human capital and accept the outside offer, rather than remain in the current occupation and preserve their human capital.

With probability $1-p$ workers cannot accept the offer z_2, even if they want to. This parameter should be thought of as a stochastic cost of switching occupations. Explicit modeling of these costs appears to complicate the environment without yielding additional insights.

At the end of each period some workers are displaced from their occupations for exogenous reasons. This happens with probability κ per period. Displaced workers have no choice but to accept an offer, z_2, from a new occupation. As the discussion of the data illustrated, there is a substantial difference between gross and net occupational mobility rates in the data. Introducing the parameter κ will allow us to account for this difference.

Consider the decision problem of an individual with age j in this economy. Denote by s

the outside offer that an individual will observe at the beginning of the following period. Let $V_j(o, z_1, z_2)$ be the value of starting the period with o units of occupation-specific human capital in an occupation with productivity level z_1 and with the observation, z_2, of the productivity level in another occupation:

$$\begin{aligned} V_j(o, z_1, z_2) &= w(S(o), G(j), z_1) + \beta(1-p)(1-\kappa)\int\int V_{j+1}(o', z_1', s)Q(z_1, dz_1')\xi(ds) \\ &+ \beta\kappa\int\int V_{j+1}(1, z_2', s)Q(z_2, dz_2')\xi(ds) \\ &+ \beta p(1-\kappa)\max_{stay,\, leave}\{\int\int V_{j+1}(o', z_1', s)Q(z_1, dz_1')\xi(ds), \\ &\qquad\qquad \int\int V_{j+1}(1, z_2', s)Q(z_2, dz_2')\xi(ds)\}, \end{aligned} \tag{7}$$

where $V_{j+1}(\cdot,\cdot,\cdot) = 0$ for $j = J$.

Definition. A stationary equilibrium consists of value functions $V_j(o, z_1, z_2)$ for all j that satisfy the Bellman equation 7.

4 Quantitative Analysis

4.1 Calibration Details

In this subsection we describe the calibration procedure for the benchmark parameters of the model. These parameters are calibrated to the late 1960s data. In the following subsection we detail the main experiment that is conducted in the calibrated model.

We chose the model period to be one year. Since we calibrate N - the number of offers that individuals receive within a year, and since very few individuals switch occupations multiple times within a year (see Hagedorn, Kambourov, and Manovskii (2004)), we do not impose unreasonable constraints on the search behavior by not considering a shorter model period. In addition, this choice of the model period substantially shortens computing time and makes it easier to compare the model with the the data that also has annual frequency. We assume that workers enter the labor market at the age of 18, and work for 45 years. We set $\beta = 1/(1+r)$, where r represents an annual interest rate of 4%.

Human capital accumulation. The growth rate of occupation specific human capital,

$f_s(o)$, is given by two linear functions:

$$f_s(o) = \begin{cases} a_s + b_s o & \text{if } o \leq \bar{o} \\ c_s + d_s o & \text{if } o \geq \bar{o}. \end{cases}$$

In this specification $\bar{o}$ is defined as the period of specific human capital experience at which the stock of specific human capital stops growing, i.e. $f_s(\bar{o}) = 1$. From then on it is declining. Given this, the $f_s(o)$ function is completely determined by its value in period 1, $f_s(1)$, its value in the next to last period, $f_s(O-1)$, and $\bar{o}$.

The growth rate of general human capital, $f_g(j)$, is defined similarly:

$$f_g(j) = \begin{cases} a_g + b_g j & \text{if } j \leq \bar{j} \\ c_g + d_g j & \text{if } j \geq \bar{j}. \end{cases}$$

The stock of general human capital ceases to grow at age $\bar{j}$, i.e., $f_g(\bar{j}) = 1$. This function can also be summarized by its value in period 1, $f_g(1)$, its value in the next to last period, $f_g(J-1)$, and $\bar{j}$.

Total human capital is given by

$$h(o, j) = \theta S(o) + (1-\theta) G(j), \tag{8}$$

where θ is the weight on specific human capital.

Stochastic Process. The idiosyncratic occupational productivity shocks z are assumed to evolve according to the following AR(1) process:

$$\ln(z') = \alpha + \phi \ln(z) + \epsilon', \tag{9}$$

where $\epsilon' \sim N(0, \sigma_\epsilon^2)$ and $0 < \phi < 1$. 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.

Therefore, there are thirteen parameters left to be calibrated - σ_ϵ^2, ϕ, $f_g(1)$, $f_g(J-1)$, $\bar{j}$, $f_s(1)$, $f_s(O-1)$, $\bar{o}$, θ, p, κ, N_e, and N. We postulate that there was a gradual change in the environment over the 1970-2004 period and assume that the only parameters that were changing are ϕ, σ_ϵ^2, κ, and α. The remaining parameters we treat as being invariant over the period.

Below we discuss two calibration strategies that depend on the information structure that we assume. First, we discuss the calibration strategy convenient under the assumption that workers are continuously surprised by the changes in the environment occurring each year. Immediately following that we describe the calibration strategy convenient under the assumption that workers fully anticipate all the changes that will occur in the future.

4.2 Experiment under the Limited Information Assumption

In this Section we assume that the values of ϕ, σ_ϵ^2, κ, and α were changing over the 1970-2004 period and each change was a surprise to the workers.

Under this assumption, calibrating the transition path of the economy involves calibrating 136 parameters (i.e., values of ϕ, σ_ϵ^2, κ, and α an each of the 34 years of the transition) in addition to the values of nine invariant parameters ($f_g(1)$, $f_g(J-1)$, $\bar{j}$, $f_s(1)$, $f_s(O-1)$, $\bar{o}$, θ, p, N_e, and N). A complication is introduced by the fact that when ϕ or σ_ϵ^2 change, the distribution of occupations over productivity levels becomes non-stationary, and thus the decision rules of workers are different across all cohorts. This makes the computational problem rather difficult.

We start by assuming that the economy was in stationary equilibrium in the late 1960s. Under this assumption all cross-sectional profiles are equivalent to the cohort-based profiles. Thus, σ_ϵ^2, ϕ, $f_g(1)$, $f_g(J-1)$, $\bar{j}$, $f_s(1)$, $f_s(O-1)$, $\bar{o}$, θ, p, κ, N_e, and N are calibrated in order to match in 1969:

1. the cross-sectional life-cycle profile of occupational mobility,
2. the cross-sectional life-cycle profile of earnings,
3. the cross-sectional life-cycle profile of earnings inequality,
4. net occupational mobility.

All the life-cycle profiles are targeted pointwise. Since there is no direct analytical relation between these parameters and the corresponding observations, we search numerically over these parameters until a good fit is found. The parameter values that generate the best fit (at the time of writing this draft of the paper) are summarized in Table 5.

Having calibrated the time-invariant parameters and the 1969 values of of ϕ, σ_ϵ^2, κ, and α, we are left with calibrating the values of this parameters over the 1970-2004 period. Given some guess for the time path of values of these four parameters we compute forward the transitional path of the economy for the cross-section of cohorts present in the market in 1970 and all the newly entering cohorts. The relative size of each cohort is parameterized to be consistent with the data (this is important for a proper accounting for the changes in inequality and aggregate productivity over the transition). Using the transitional simulated data for a cross-section of cohorts, we update the time paths for ϕ, σ_ϵ^2, κ, and α, to match year-by-year over the 1970-2004 period the time paths of:

1. gross occupational mobility,
2. net occupational mobility,
3. cross-sectional average wages,
4. correlation in changes in occupational employment shares.

Targeting separately the time path of the gross and net occupational mobility identifies the contribution of the increase in volatility of occupational productivity shocks governed by ϕ and σ_ϵ^2 and a change in the idiosyncratic destruction in occupational matches governed by κ. Targeting the time path of cross-sectional average wages helps identify the contribution of macroeconomics factors, such as the slowdown of productivity growth, to profiles' flattening. The last target measures changes over time in the correlation of the changes in occupational employment shares in each two consecutive years. It identifies the time path of the persistence of productivity (demand) shocks to occupations. Note that we *do not* target life-cycle profiles of earnings and earnings inequality.

We study the implications of these changes for the flattening of the life-cycle profiles of earnings, steepening of the life-cycle profiles of earnings inequality, the dynamics of cross-sectional earnings inequality over the transition, and the dynamics of earnings stability over the transition.

4.3 Experiment under the Full Information Assumption

In this Section we do not assume that economy is in steady state at any point. We allow the values of ϕ, σ_ϵ^2, κ, and α to change at any point in time and assume that workers know the full path of these parameters.[11]

First, we guess on a time paths of ϕ, σ_ϵ^2, κ, and α over the 1924 (=1969-45) - 2047 (=2004+45-1-1) period. Note that this is the only time period during which the behavior of the cohorts we are interested in (the ones present in the labor market over the 1969-2004 period) may be affected by the labor market conditions. We also guess on the values of the time-invariant parameters $f_g(1)$, $f_g(J-1)$, $\bar{j}$, $f_s(1)$, $f_s(O-1)$, $\bar{o}$, θ, p, N_e, and N.

Second, we define a grid for the values of the occupational productivity levels, z, and find the distribution ζ of occupations over productivity levels in 1924.[12] Given the postulated time paths of ϕ, σ_ϵ^2, and α, we compute the time-varying transition function $Q_t(z,\cdot)$. Finally, given the 1924 distribution, ζ_{1924} and $Q_t(z,\cdot)$, we update forward the distributions of occupations over productivity shocks, ζ_t, in every year throughout 1925-2047. This, in turn, implies a sequence of the maximal offer distributions ξ_t.

Third, we compute backwards the value and policy functions for all the cohorts entering the labor market from 1924 through 2004. Since each cohort has a different labor market experience, these functions are different for each cohort.

Fourth, we compute forward the transitional path of the economy by simulating behavior of all the cohorts present in the market in 1969 and all the newly entering cohorts. The relative size of each cohort is parameterized to be consistent with the data (this is important for a proper accounting for the changes in inequality, mobility, and aggregate productivity over the transition).

[11] Calibrating the model under the assumption that workers have perfect information regarding future changes in the environment is complicated by the fact that workers' expectations about the changes in the environment that have not yet happened need to be measured. However, the model is identified even in this case. The idea is as follows. An expected change in the environment in, say, year 2049 affects the behavior of the cohort entering labor market in 2005, but no one else's (since workers are present in the market for 45 years only). A change expected to take place in 2048 affects the behavior of the cohorts entering labor market in 2004 and 2005, but no one else's. And so on.

[12] We assume that this distribution is given by the stationary distribution implied by the AR(1) process $\ln(z') = \alpha + \phi \ln(z) + \epsilon'$, where σ_ϵ^2 and ϕ are given by their guessed 1924 values and α is normalized to zero.

Fifth, we collect the data from the simulated model trying to replicate the way in which the data motivating this paper was collected. In particular, we pretend that we observe our model economy only over the 1969-2004 period. We collect a sample of individuals present in the labor market during (parts of) that period. Using the collected sample we obtain the following statistics.

1. Estimate the following regression model that summarizes the cohort-based changes in occupational mobility:

$$m_{it} = \beta_0 + \beta_1 z_i + \beta_2 z_i^2 + \beta_3 z_i * x_{it} + \beta_4 x_{it} + \beta_5 x_{it}^2 + \beta_6 x_{it}^3 + \epsilon_{it}, \tag{10}$$

   where m_{it} is the probability of an occupational switch for a member of cohort i in period t, x_{it} is the age of cohort i in period t, z_i is the entry year of cohort i, and ϵ_{it} is a white noise term.

2. The time-path of net occupational mobility. Targeting separately the time path of the gross (implicit in the cohort-based regression above) and net occupational mobility identifies the contribution of the increase in volatility of occupational productivity shocks governed by ϕ and σ_ϵ^2 and a change in the idiosyncratic destruction in occupational matches governed by κ.

3. Estimate of the following wage regression:

$$\begin{aligned} \ln w_{it} = \beta_0 \quad &+ \quad \beta_1 Occ\_Ten_{it} + \beta_2 Occ\_Ten_{it}^2 + \beta_3 Occ\_Ten_{it}^3 \\ &+ \quad \beta_4 Work\_Exp_{it} + \beta_4 Work\_Exp_{it}^2 + \beta_4 Work\_Exp_{it}^3 + \epsilon_{it}, \end{aligned} \tag{11}$$

   where w_{imt} is the real hourly wage of person i in period t. Occ_Ten denotes tenure in the current occupation. $Work\_Exp$ denotes overall labor market experience. The model is estimated using the ordinary least squares.[13]

[13] We will compare the estimates to those obtained on the PSID data using the same estimation method. It is well recognized in the literature that (1) the quality of occupational match is likely correlated with occupational tenure, and (2) the quality of occupational match increases on average with labor market experience. These two effects tend to bias (in opposing directions) estimated returns to occupational experience. We do not attempt to correct for this bias because identical bias is present in the estimates obtained on the PSID data and in the model.

4. For the cohort entering the labor market in 1963 only estimate the life-cycle earnings profile from the following regression:

$$\ln w_t = \beta_0 + \beta_1 Work\_Exp_t + \beta_2 Work\_Exp_t^2 + \beta_3 Work\_Exp_t^3 + \epsilon_{it}, \tag{12}$$

   where w_{it} is log average real annual earnings of that cohort in period t, x_t is the age of members of the cohort in period t, and ϵ_{it} is a white noise term.

5. For the cohort entering the labor market in 1963 only estimate the life-cycle inequality profile from the following regression:

$$ineq_t = \beta_0 + \beta_1 Work\_Exp_t + \beta_2 Work\_Exp_t^2 + \beta_3 Work\_Exp_t^3 + \epsilon_{it}, \tag{13}$$

   where $ineq_{it}$ is a measure of inequality of earnings (e.g., the standard deviation of log earnings) of that cohort in period t, x_t is the age of members of the cohort in period t, and ϵ_{it} is a white noise term.

   The last three targets help identify parameters of the human capital accumulation functions - $f_g(1)$, $f_g(J-1)$, $\bar{j}$, $f_s(1)$, $f_s(O-1)$, $\bar{o}$, θ, and parameters governing the efficiency of the search process - p, N_e, and N. These parameters, of course, are not independent of the estimates of ϕ, σ_ϵ^2, κ, and α.

6. The time-path of cross-sectional average wages. This target helps identify the contribution of macroeconomics factors, such as the slowdown of productivity growth, to profiles' flattening.

7. The time-path of correlation in changes in occupational employment shares. This targets identifies the time path of the persistence of productivity (demand) shocks to occupations.

We compare the set of statistics obtained above to the similar statistics obtained in the data. We update the guesses for the parameters until we obtain the closest correspondence between the statistics in the model and in the data. Note that we *do not* target life-cycle profiles of earnings and earnings inequality in this procedure.

5 Results from the Calibrated Model

5.1 Benchmark Calibration

Figure 17 describe the extent to which the model matches the targets in the benchmark calibration. We targeted the cross-sectional life-cycle earnings profile, the profile of earnings inequality, and the profile of occupational mobility in the late 1960s. At this point the calibration is still preliminary, but we can see that the model matches important features of the data. We are able to capture the earnings profile although the increase in the model is initially higher than in the data. In terms of the profile of earnings inequality, the model matches the initial decline in inequality and its subsequent increase. Finally, the model generates the decline in the profile of occupational mobility with age, but the decline is concentrated in the first few years only. The aparent inability of the model to generate a strong life-cycle effect in occupational mobility is currently our major concern.

5.2 Steady State with Higher Volatility

Figure 18 tells us how life-cycle profiles of earnings, earnings inequality, and occupational mobility change as we increase the variance of the idiosyncratic shocks to occupations, decrease their persistence, and increase the idiosyncratic occupational displacement. The new parameter values are summarized in Table 6. This is a hypothetical steady state comparison. We provide this results just to develop intuition. The parameters of the second steady state are not calibrated and in our full analysis we do not even assume that such a steady state exists. Under these new parameter values, the model matches the cross-sectional facts on gross and net occupational mobility in the mid-1990s in Table 7. These results indicate that the model can eventually go a long way toward explaining the flattening in the earnings profile, the steepening in the profile of earnings inequality, and the upward shift in the profile of occupational mobility.

5.3 Dissecting the Effects

In this subsection we analyze the effects that changes in κ, σ_ϵ^2, and ϕ have on the results. The discussion is somewhat imprecise because of the multitude of the effects in the model that a change of each of these parameters entails. We concentrate on the key effects.

5.3.1 Changes in κ

Suppose the only change in the environment was an increase in the rate of idiosyncratic destruction of occupational matches, κ. How would this affect life-cycle profiles of earnings, inequality and mobility? The results of this experiment are described in Figure 19. An increase in κ directly exogenously increases occupational mobility of workers of all ages. As one may expect, in equilibrium with higher κ life cycle profiles of earnings are flatter. This happens because workers are forced to switch careers more often and this leads to a slower growth of the average level of human capital over the life-time of a cohort. In addition, an increase in κ is akin to an increase in the discount rate and this leads to a decline in the incentives to sort to higher paying occupations. This last effect further flattens life-cycle earnings profiles but slightly dampens the increase in mobility. A stronger increase of wage inequality with age occurs because higher κ leads to a higher dispersion of human capital with age.

5.3.2 Changes in σ_ϵ^2

Suppose the only change in the environment was an increase in σ_ϵ^2. How would this change affect life-cycle profiles of earnings, inequality and mobility?

Before presenting the evidence from the model, it is instructive to consider a simple example. Suppose there are just two occupations and two possible productivity levels, high and low. Productivity shocks switch each period, so that an occupation with a high productivity today will have low productivity tomorrow. Shocks are perfectly negatively correlated across occupations, so that when one occupation has high productivity, the other one has low. Suppose that individuals are initially equally distributed across these two occupations. Individuals exogenously accumulate human capital while staying in their occupation. Human capital is specific and is destroyed upon each occupational switch.

Case 1. The difference between high and low productivities across occupations is small relative to the increase in worker's productivity due to the accumulation of human capital. In this case, despite fluctuating productivity levels, most workers will choose not to switch their occupations and to preserve their human capital. Life-cycle profile of earnings will mimic the human capital accumulation function.

Case 2. Suppose the variance of productivity levels increases, i.e., the distance between high and low productivities across occupations becomes large. Now, despite the destruction of human capital upon each switch, with variance sufficiently high, workers from a given cohort will switch their occupations each period. Thus the life-cycle profile of earnings will be perfectly flat.

These two extreme cases illustrate the essence of the relationship between the variance of productivity shocks to occupations, occupational mobility, and the life-cycle earnings profiles. The complete relationship between σ_ϵ^2 and the profiles of interest is more complicated in our model. The results of the experiment of raising σ_ϵ^2 are described in Figure 20. As can be seen, an increase in variance actually steepens life-cycle profiles of earnings. This happens because of the increase in sorting at the beginning of life that higher variance generates. The increase in inequality with age is smaller because the support of productivity levels of occupations on which workers end up working is smaller.

Note: May separate out and discuss the effect in the first period of life to make the example a bit more relevant and insightful for what actually goes on.

5.3.3 Changes in ϕ

Suppose, finally, that the only change in the environment was an increase in persistence of occupational productivity shocks ϕ. How would it affect life-cycle profiles of earnings, inequality and mobility? The results of this experiment are described in Figure 21. More discussion will be added later, but a brief pause will convince the reader that the effects are the exact opposite of the ones described in the case of the increase in variance. They do depend on the initial level of ϕ, however.

5.4 Changes in Life-Cycle Profiles over the Transition

Here we follow the changing life-cycle profiles over the transition. The economy is assumed to be in a steady state prior to 1970. In 1970 the parameter values for ϕ, σ_ϵ, κ, and α begin to change gradually over time. We assume, from now, that all changes in the environment are unexpected. The time paths of targets and calibrated parameters will be reported in the next draft. The resulting life-cycle profiles of earnings, inequality, and occupational mobility for several cohorts living through the transition seem consistent with the observations in the data motivating this paper. More formally, in the next draft we will estimate the same regression model 1 as we estimated in the data, and compare the significance of profiles' changes over time.

5.5 Accounting for the Slowdown of Productivity Growth

It is well known that aggregate productivity growth rate was below its trend between the mid-1970s and mid-1990s. Measured productivity in the model is partially endogenous because it is affected by the average amount of human capital and by the distribution of workers across occupations. In addition, the paths of productivity and inequality depend on the age composition of the population. We are able to disentangle all these effects in the calibrated model.

6 Discussion and Sensitivity Analysis

6.1 Evaluating Alternative Theories of the Increase in Occupational Mobility

It may be argued that the increase in occupational mobility was driven not by a change in the process generating idiosyncratic occupational productivity shocks but by a decline in the cost of switching occupations. There are two ways in which a decline in the search cost can be thought of in the model. First, these costs will decline if human capital has become less specific over time. In order to evaluate this hypothesis, we change the parameters of the human capital accumulation functions in the model calibrated for the 1960s, in order to infer whether such a change is consistent with the data. We expect that the decline in the specificity of human capital (modeled as a decline in $f_s(1)$) will lead to an increase in occupational mobility and a flatter life-cycle earnings profile in the model, but, everything else equal, will counterfactually result in a lower wage dispersion. This intuition is confirmed in Figure 22.

A second way to model a decline in search costs is to increase the value of the parameter p. The results of this experiment are summarized in Figure 23.

Alternatively, one may argue that search has become more directed over time. This would occur, for example, if there was an increase in the amount of information regarding sectors in the economy that are experiencing high productivity. An increase in workers' information about outside opportunities, that has an effect of making search more directed, maps into an increase in the value of parameter N. More directed search in the beginning of life - higher N_e - will likely result in lower mobility, however. The results of these experiments will be provided in a future draft.

These last few results should provide insight and be relevant to policy makers because they indicate the effectiveness of government policies in helping workers adapt better to changes in the labor market. Some potentially beneficial government policies are reducing the cost of switching occupations, increasing the amount of information regarding sectors in the economy that are experiencing high productivity shocks, and helping with the occupational retraining of the labor force during occupational switches.

6.2 Discussion of Modeling Choices

Capital Mobility. We have assumed a very simple production technology that appears to abstract from capital mobility. Here we show that the results carry over to a richer equilibrium model that explicitly allows for capital reallocation across occupations. Assume that all occupations produce the same homogeneous good. Output y in an occupation is produced with the production technology

$$y = F(L, K, z) = zL^{\alpha}K^{1-\gamma}, \tag{14}$$

where L denotes the total amount of effective labor in occupation, K represents the total amounts of capital supplied to the production of output in that occupation, $\alpha + \gamma = 1$, and z denotes the idiosyncratic productivity shock. These shocks follow a Markov process characterized by the transition function $Q(z, \cdot)$. Realizations of z are independent across islands. The Markov process for z is assumed to possess an invariant distribution ζ that satisfies $\zeta(Z) = \int Q(z, Z)\zeta(dz)$, where Z denotes sets of idiosyncratic productivity shocks.

The spot factor markets in every occupation are assumed to be competitive. Thus wages are given by the marginal productivities of each type of labor and return on capital is given by its marginal product. Physical capital is owned by workers who lend capital to firms. Since we study only the life-cycle profiles of *earnings* in this paper and because workers are assumed to be risk-neutral, without loss of generality, we do not explicitly model the distribution of capital holdings. Capital is assumed to be perfectly mobile across occupations, and thus its rental rate, r, is equalized across them. This implies that the amount of capital allocated to an occupation with total supply of effective labor equal to L is given by

$$K = \left[\frac{r}{z\gamma}\right]^{\frac{1}{\gamma-1}} L. \tag{15}$$

Wages for a worker with total amount of human capital h_i are then given by

$$w_i = h_i z^{\frac{1}{1-\gamma}} \left[\frac{r}{\gamma}\right]^{\frac{\gamma}{\gamma-1}}. \tag{16}$$

Note that, with the constant returns production function, costless and instantaneous capital mobility makes wages in an occupation independent of the measure and of the age and human capital distribution of workers in that occupation. Thus, given the rental rate, r, an occupation is now fully characterized by the value of its productivity, z.

The exposition above implies that without the loss of generality we can assume that each worker owns the production technology, so that:

$$y_i = w_i = \tilde{z}_i h_i, \tag{17}$$

This is equivalent to the model we have studied in this paper.

Learning-by-Doing. We have assumed that human capital accumulation occurs through exogenous learning-by-doing. Manovskii (2003) shows that the model is easily modified to incorporate human capital accumulation that requires active investments of time in the learning process. The effect on training decisions of the change in economic environment we have described is potentially interesting and is complementary to the effects we study in this paper. There is little evidence, however, to direct our choice of modeling the human capital accumulation technology. Heckman, Lochner, and Cossa (2002) suggest that learning-by-doing is more consistent with the data, and this explains our choice.

7 Conclusion

This paper contributes to the literature studying substantial changes in the US labor market since the early 1970s, in particular the rise in earnings dispersion. We first document a number of new facts important for understanding these changes. In particular, we find that since the early 1970s there was:

1. a flattening of life-cycle earnings profiles for more recent cohorts,
2. a steepening of life-cycle profiles of earnings inequality for more recent cohorts, and
3. an increase in occupational mobility for more recent cohorts.

We develop a theory that implies that these developments are intimately related.

We study quantitatively what fraction of the change in the life-cycle profiles of earnings and earnings inequality is accounted for by the economic forces that drive the increase in occupational mobility.

Preliminary results indicate that the increase in the variability of productivity shocks to occupations coupled with the increase in the rate of idiosyncratic destruction of matches from the 1960s to the 1990s, may account for all these observations. The theory we propose is consistent with other facts characterizing the changes in the labor market, such as the increase in the transitory variability of earnings.

Table 1: Flattening Life-Cycle Profiles of Earnings in the PSID Data.

	(1)	(2)	(3)	(4)	(5)
z	0.0238	0.0443	0.0212	0.0217	0.0256
	(0.0055)	(0.0119)	(0.0052)	(0.0063)	(0.0061)
z^2	-0.0007	-0.0010	-0.0006	-0.0006	-0.0007
	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
$z * x$	-0.0004	-0.0009	-0.0006	-0.0004	-0.0004
	(0.0001)	(0.0003)	(0.0002)	(0.0001)	(0.0001)
x	0.1095	0.1291	0.1002	0.1265	0.1001
	(0.0072)	(0.0127)	(0.0067)	(0.0090)	(0.0080)
x^2	-0.0034	-0.0036	-0.0033	-0.0046	-0.0029
	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0003)
x^3	0.0001	0.0001	0.0001	0.0001	0.0001
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Intercept	9.1152	8.7597	-0.2398	9.1614	1.4478
	(0.0845)	(0.1760)	(0.0791)	(0.0940)	(0.0936)
R2	0.8292	0.8364	0.7758	0.7786	0.7830
N of obs.	859	859	859	859	859

Source: Authors' calculations from the PSID.
Note - We estimate the following regression,

$$w_{it} = \beta_0 + \beta_1 z_i + \beta_2 z_i^2 + \beta_3 z_i * x_{it} + \beta_4 x_{it} + \beta_5 x_{it}^2 + \beta_6 x_{it}^3 + \epsilon_{it}$$

where w_{it} is log average real annual earnings of cohort i in period t (with the exception of Column (3), where w_{it} represents the log of the ratio of the average real annual earnings of cohort i in period t relative to the average real annual earnings of the cohort entering the labor market in period t, and Column (5), where w_{it} represents log real hourly wages), z_i is the entry year of cohort i, and ϵ_{it} is a white noise term. x_{it} is the age of cohort i in period t in columns (1), (2), (3), and (5), while in column (4) it represents years of labor market experience of cohort i in period t. The specification reported in column (2) includes a full set (minus one) of year dummy variables. The negative coefficient on the interaction of the linear age (experience) and cohort terms, $z * x$, implies that every successive cohort has a flatter earnings profile.

Table 2: Flattening Life-Cycle Profiles of Earnings in the CPS Data.

	(1)	(2)	(3)	(4)
z	0.0382	0.0527	0.0136	0.0427
	(0.0013)	(0.0025)	(0.0019)	(0.0021)
z^2	-0.0008	-0.0009	-0.0003	-0.0008
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$z * x$	-0.0008	-0.0011	-0.0002	-0.0010
	(0.0001)	(0.0001)	(0.0000)	(0.0001)
x	0.1193	0.1324	0.0789	0.1602
	(0.0018)	(0.0027)	(0.0026)	(0.0032)
x^2	-0.0032	-0.0032	-0.0022	-0.0056
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
x^3	0.0001	0.0001	0.0001	0.0001
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Intercept	8.8135	8.5531	-0.1109	8.7042
	(0.0216)	(0.0396)	(0.0304)	(0.0329)
R2	0.9731	0.9834	0.9107	0.9473
N of obs.	1089	1089	1089	1082

Source: Authors' calculations from the CPS.
Note - We estimate the following regression,

$$w_{it} = \beta_0 + \beta_1 z_i + \beta_2 z_i^2 + \beta_3 z_i * x_{it} + \beta_4 x_{it} + \beta_5 x_{it}^2 + \beta_6 x_{it}^3 + \epsilon_{it}$$

where w_{it} is log average real annual earnings of cohort i in period t (with the exception of Column (3), where w_{it} represents the log of the ratio of the average real annual earnings of cohort i in period t relative to the average real annual earnings of the cohort entering the labor market in period t), z_i is the entry year of cohort i, and ϵ_{it} is a white noise term. x_{it} is the age of cohort i in period t in columns (1), (2), and (3), while in column (4) it represents years of labor market experience of cohort i in period t. The specification reported in column (2) includes a full set (minus one) of year dummy variables. The negative coefficient on the interaction of the linear age (experience) and cohort terms, $z * x$, implies that every successive cohort has a flatter earnings profile.

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

	1969-72	1990-93	Change
Gini Coefficient	0.264	0.330	25.0%
Variance of permanent log wages, $var(\pi_i)$	0.178	0.230	29.2%
Average variance of transitory log wages, average $var(\eta_i)$	0.110	0.172	56.4%
Occupational mobility	0.165	0.205	24.2%

Note - Authors' calculations from the PSID. For sample restrictions, see Section 2. As discussed in Section 2.1.4, the second and third lines present the decomposition of log wage (purged of education and age effects) variance into permanent and transitory components using the Gottschalk and Moffitt (1994) procedure for the 1970-78 and 1979-87 periods. Occupational mobility refers to the average annual rate of occupational mobility over the corresponding time period. See Kambourov and Manovskii (2004b) for details of the estimation procedure.

Table 4: Occupational Specificity of Human Capital.

	Returns to Experience		
	2 years	5 years	10 years
Occupation	.0535	.1188	.1900
	(.0068)	(.0154)	(.0258)
Industry	-.0030	-.0086	-.0207
	(.0071)	(.0149)	(.0226)
Employer	.0012	.0027	.0079
	(.0096)	(.0136)	(.0212)

Source: Kambourov and Manovskii (2008a). Returns to experience represent the percentage increase in wages due to the first 2, 5, or 10 years of occupational, industry, or employer tenure. Standard errors are in parentheses. The results are computed from the estimates of the following econometric model:

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

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

Table 5: Parameter Values in Benchmark Calibration.

ϕ	σ_ϵ	p	κ	θ
0.89	0.19	0.36	0.008	0.69

$f_g(1)$	$f_g(J-1)$	$\bar{j}$	$f_s(1)$	$f_s(O-1)$	$\bar{o}$
1.019	0.96	46.8	1.018	0.97	59

Table 6: Values of Time-Dependent Parameters.

Parameter	1968-70	1994-97
ϕ	0.89	0.83
σ_ϵ	0.19	0.3
κ	0.008	0.014

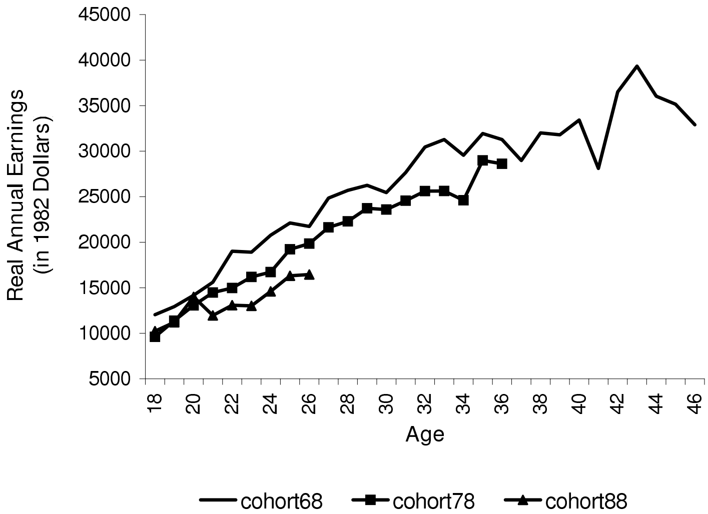
ϕ - persistence of the log shocks.
σ_ϵ - standard deviation of the white noise.

Table 7: Steady State Results.

	Results	1968-70	1994-97
1.	Gross Mobility	0.153	0.195
		(0.163)	(0.215)
2.	Net Mobility	0.08	0.095
		(0.092)	(0.134)
3.	Gini Coefficient	0.225	0.289
		(0.264)	(0.330)

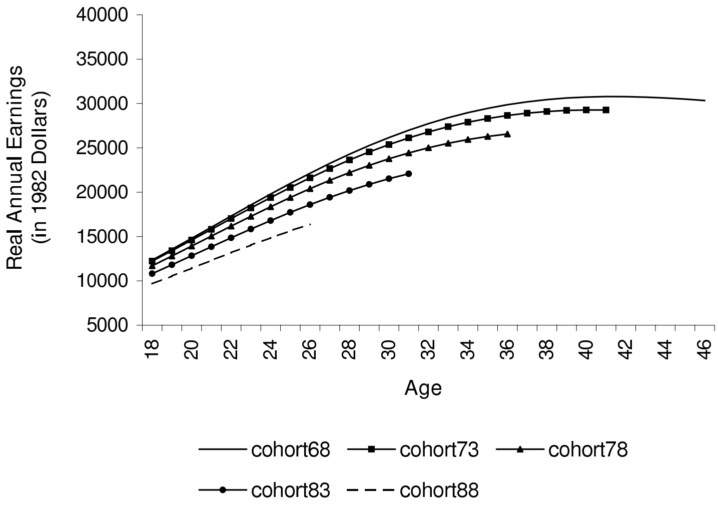
Note - Values in the data are in parenthesis.

Figure 1: Life-Cycle Earnings Profiles in the United States, Raw Data, PSID.



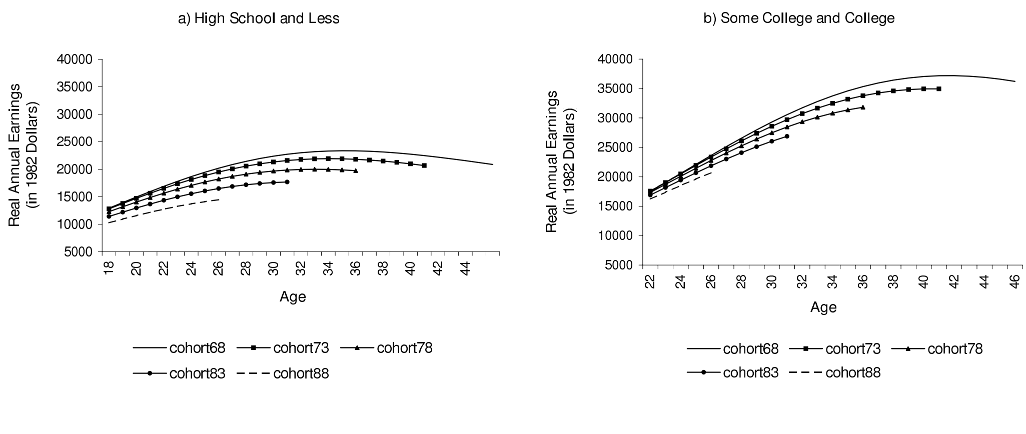
Source: Authors' calculations from the PSID.

Figure 2: Life-Cycle Earnings Profiles in the United States, Regression Smoothed, PSID.



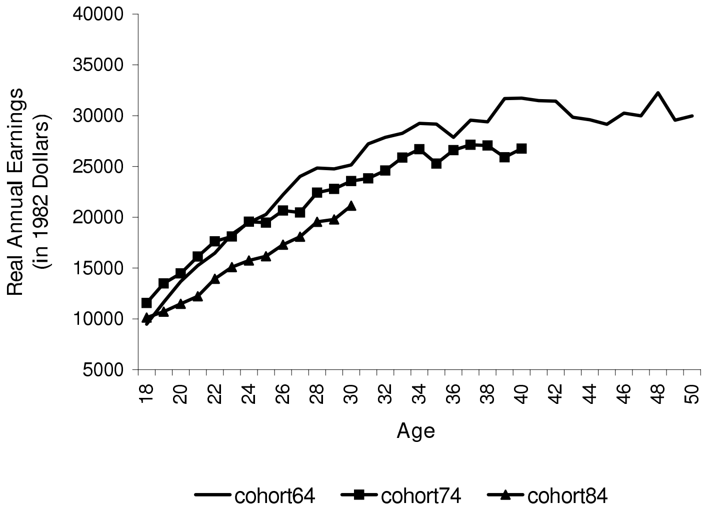
Source: Authors' calculations from the PSID.

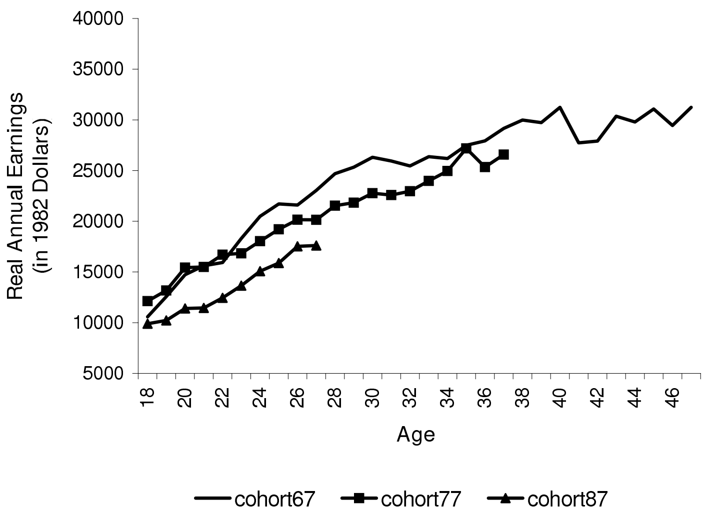
Figure 3: Life-Cycle Earnings Profiles in the United States by Education Groups, Regression Smoothed, PSID.



Source: Authors' calculations from the PSID.

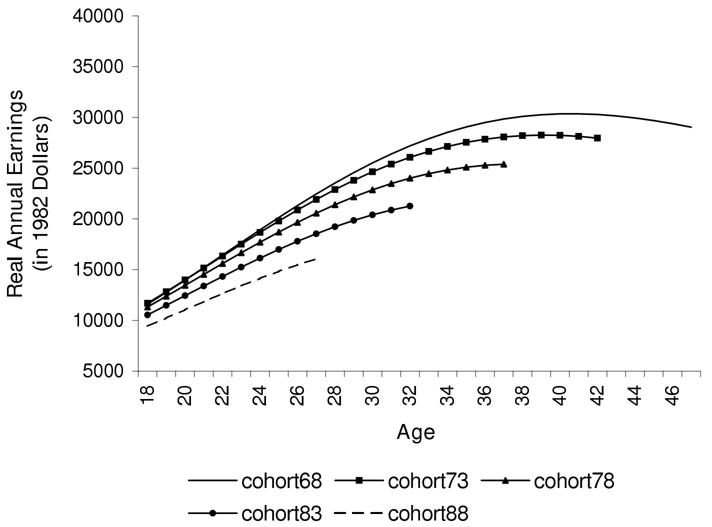
Figure 4: Life-Cycle Earnings Profiles in the United States, Raw Data, CPS.





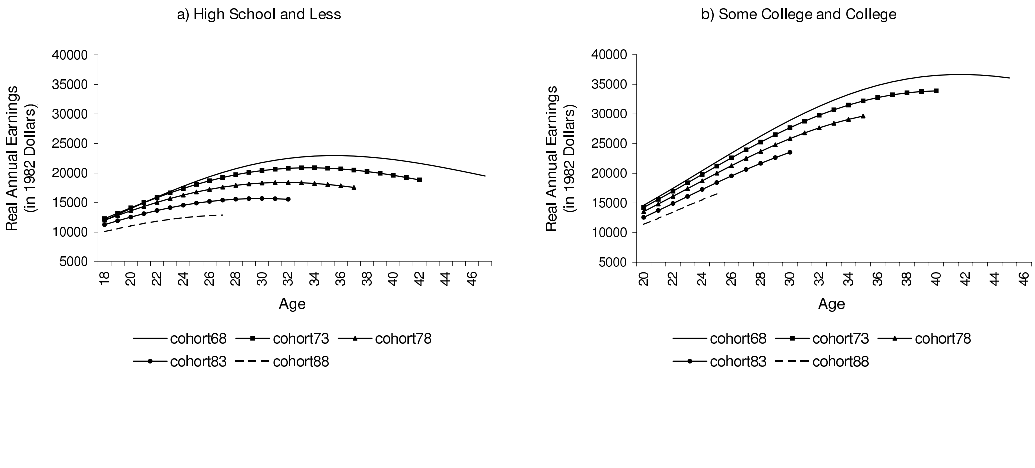
Source: Authors' calculations from the CPS.

Figure 5: Life-Cycle Earnings Profiles in the United States, Regression Smoothed, CPS.



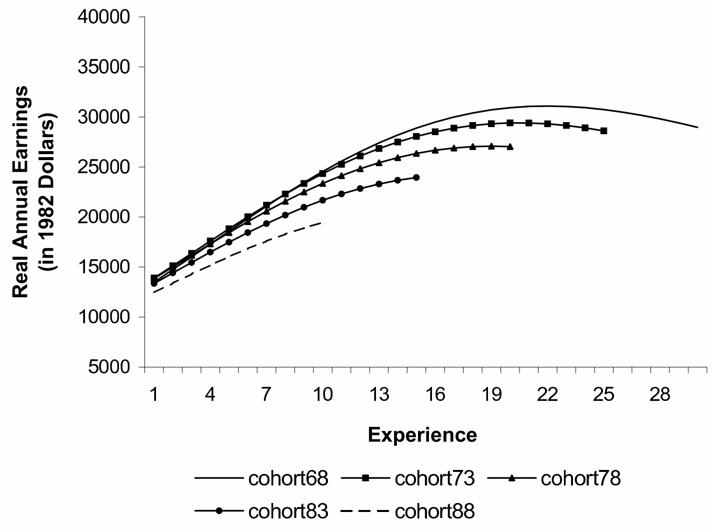
Source: Authors' calculations from the CPS.

Figure 6: Life-Cycle Earnings Profiles in the United States by Education Groups, CPS.



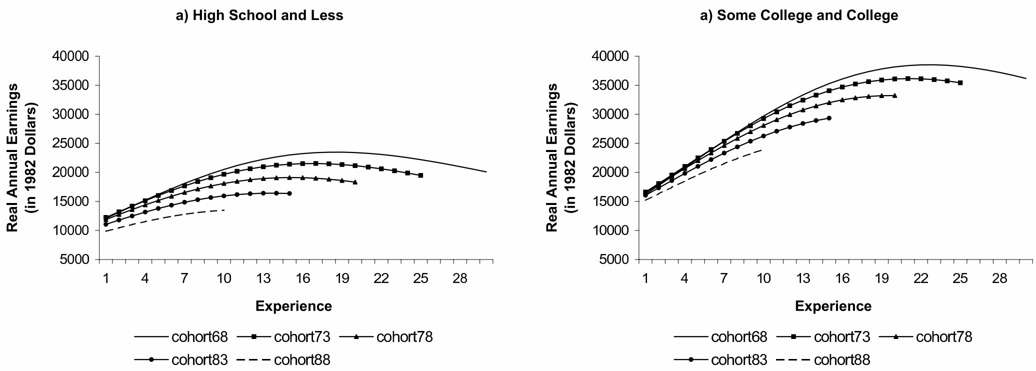
Source: Authors' calculations from the CPS.

Figure 7: Experience Earnings Profiles in the United States, CPS.



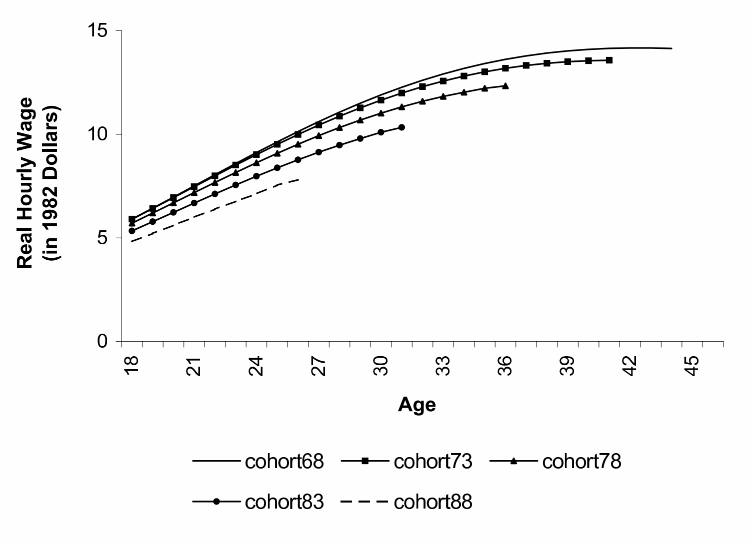
Source: Authors' calculations from the CPS.

Figure 8: Experience Earnings Profiles in the United States by Education Groups, CPS.



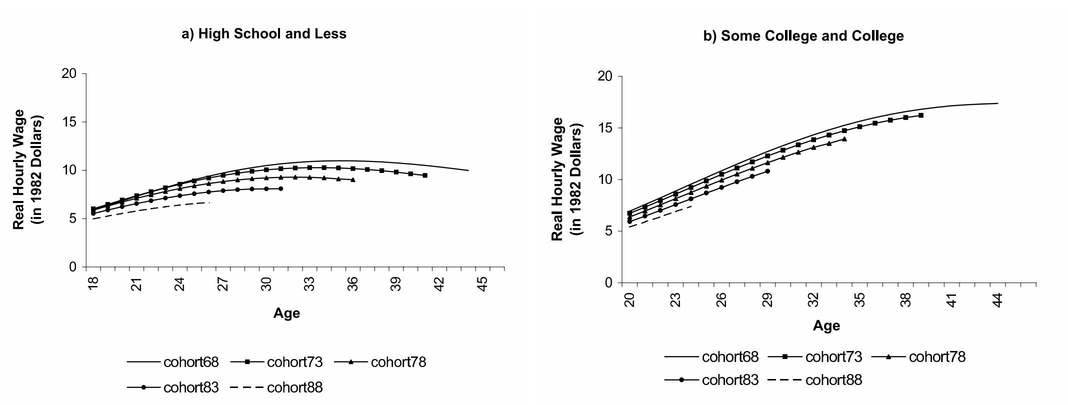
Source: Authors' calculations from the CPS.

Figure 9: Life-Cycle Hourly Wage Profiles in the United States, PSID.



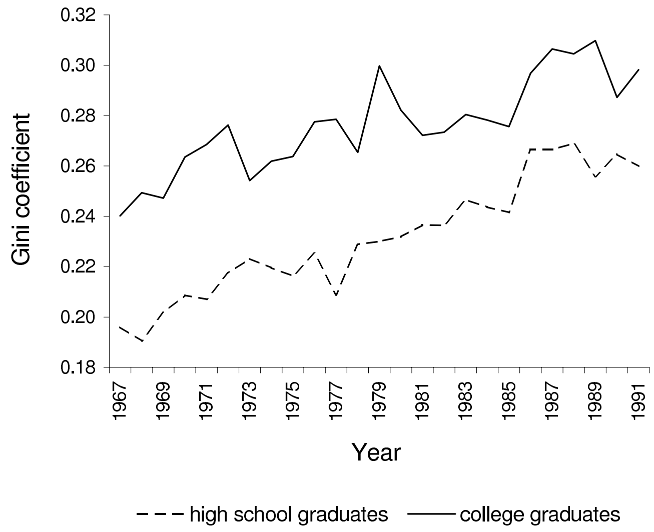
Source: Authors' calculations from the PSID.

Figure 10: Life-Cycle Hourly Wage Profiles in the United States by Education Groups, PSID.



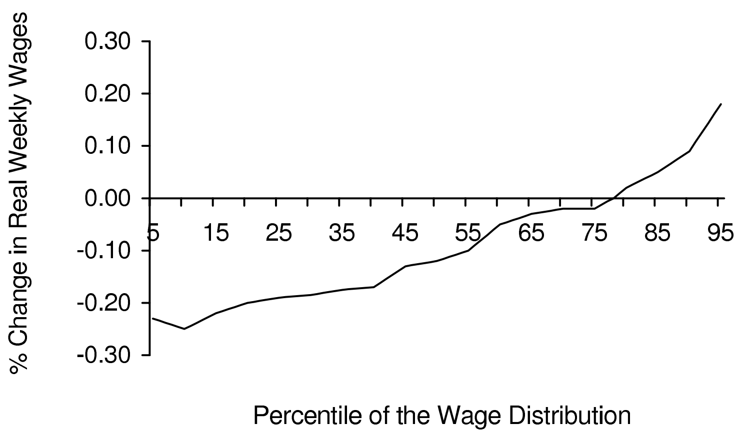
Source: Authors' calculations from the PSID.

Figure 11: The Gini Coefficient of Hourly Wages for High-School Graduates and College Graduates in the United States, 1967-1991.



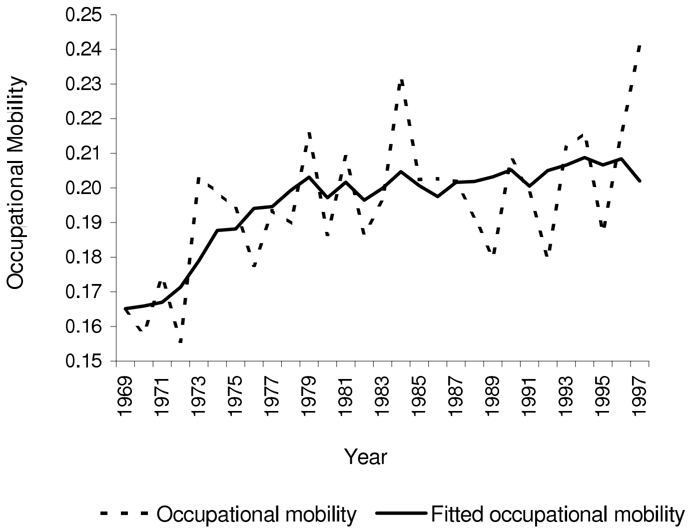
Source: Authors' calculations from the PSID.

Figure 12: Percentage Change in Real Weekly Wages by Percentiles of the Wage Distribution, 1994 vs. 1973.



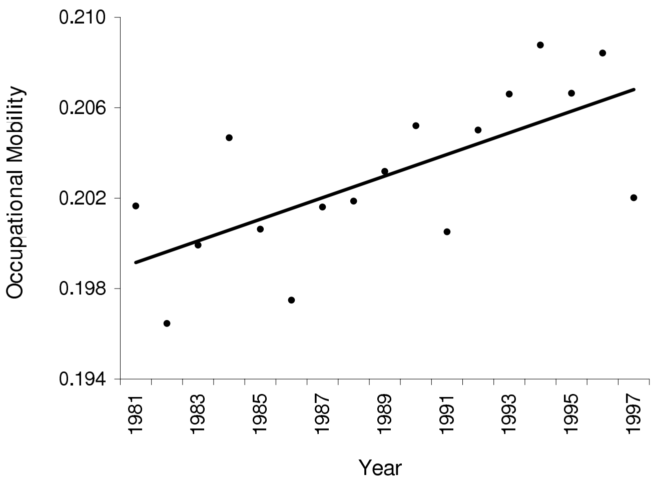
Source: Gottschalk (1997).

Figure 13: Occupational Mobility in the United States, 1969-1997, PSID.



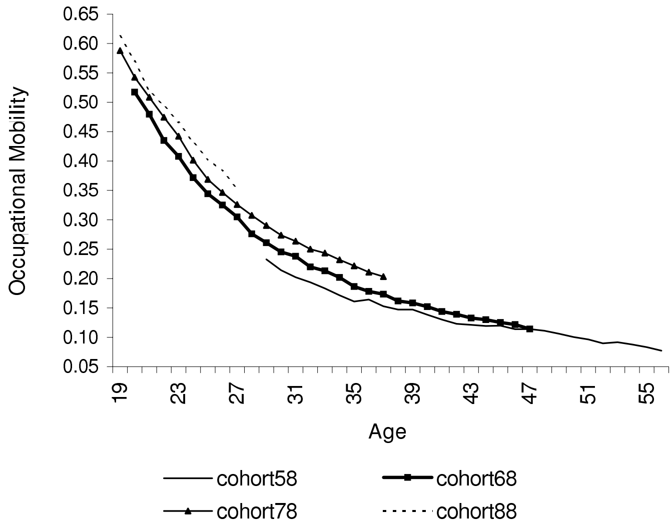
Source: Authors' calculations from the PSID.

Figure 14: Occupational Mobility in the United States, 1981-1997, PSID.



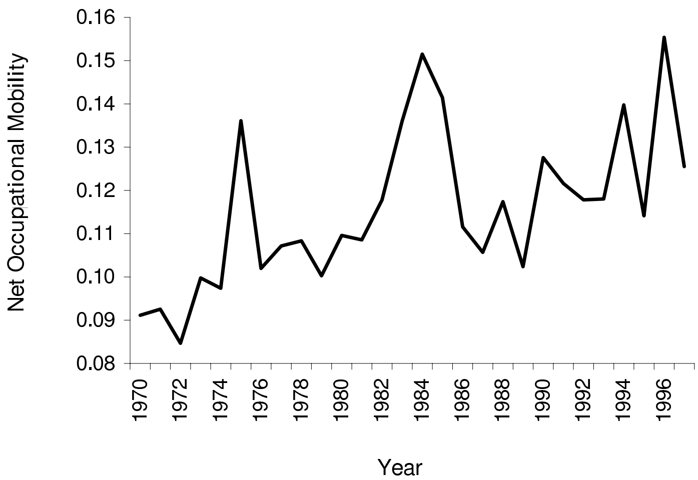
Source: Authors' calculations from the PSID.

Figure 15: Occupational Mobility in the United States by Cohorts, PSID.



Source: Authors' calculations from the PSID.

Figure 16: Net Occupational Mobility in the United States, 1970-1997, PSID.



Source: Authors' calculations from the PSID.

Figure 17: Benchmark Results.

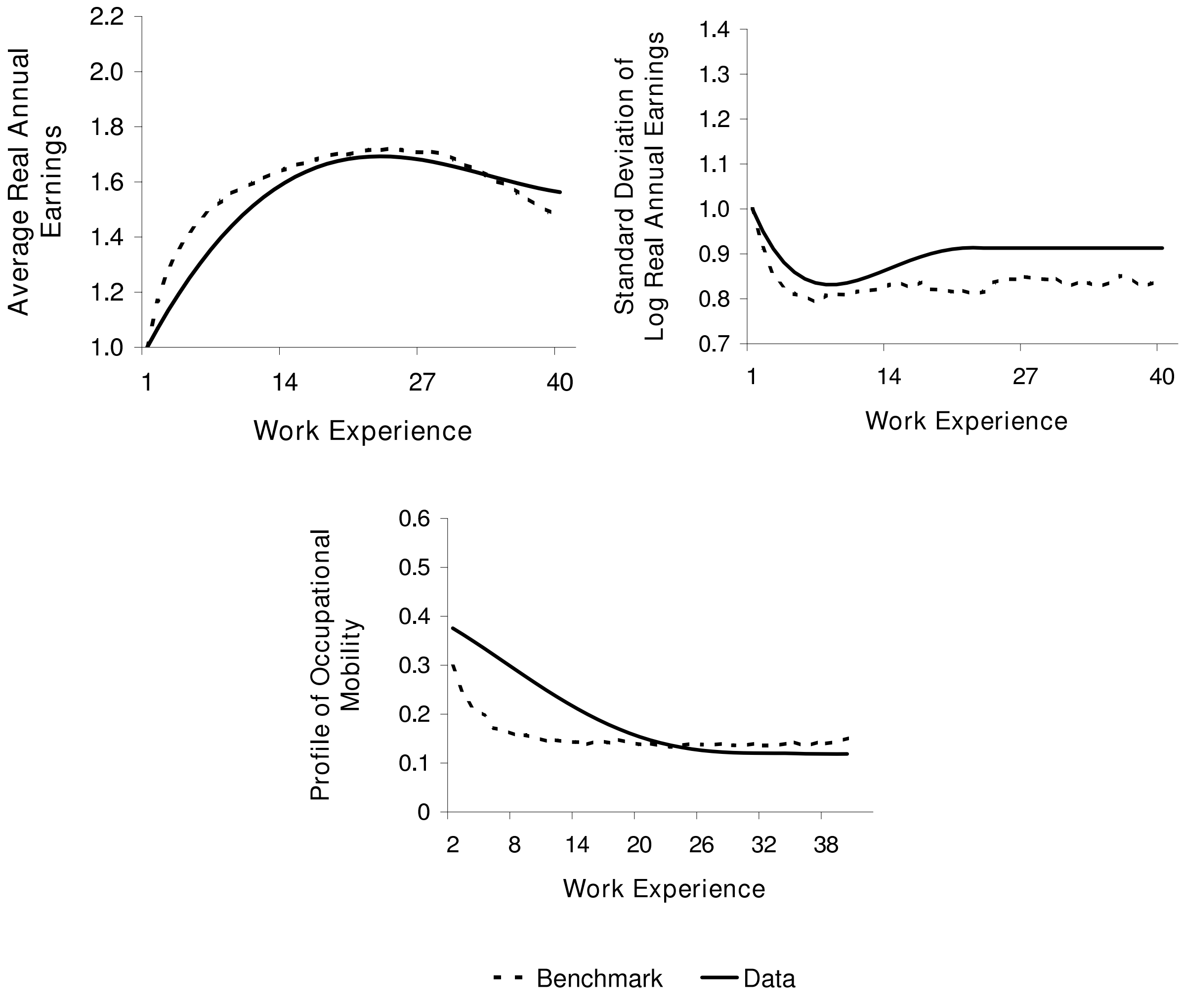


Figure 18: New Steady State Experiment.

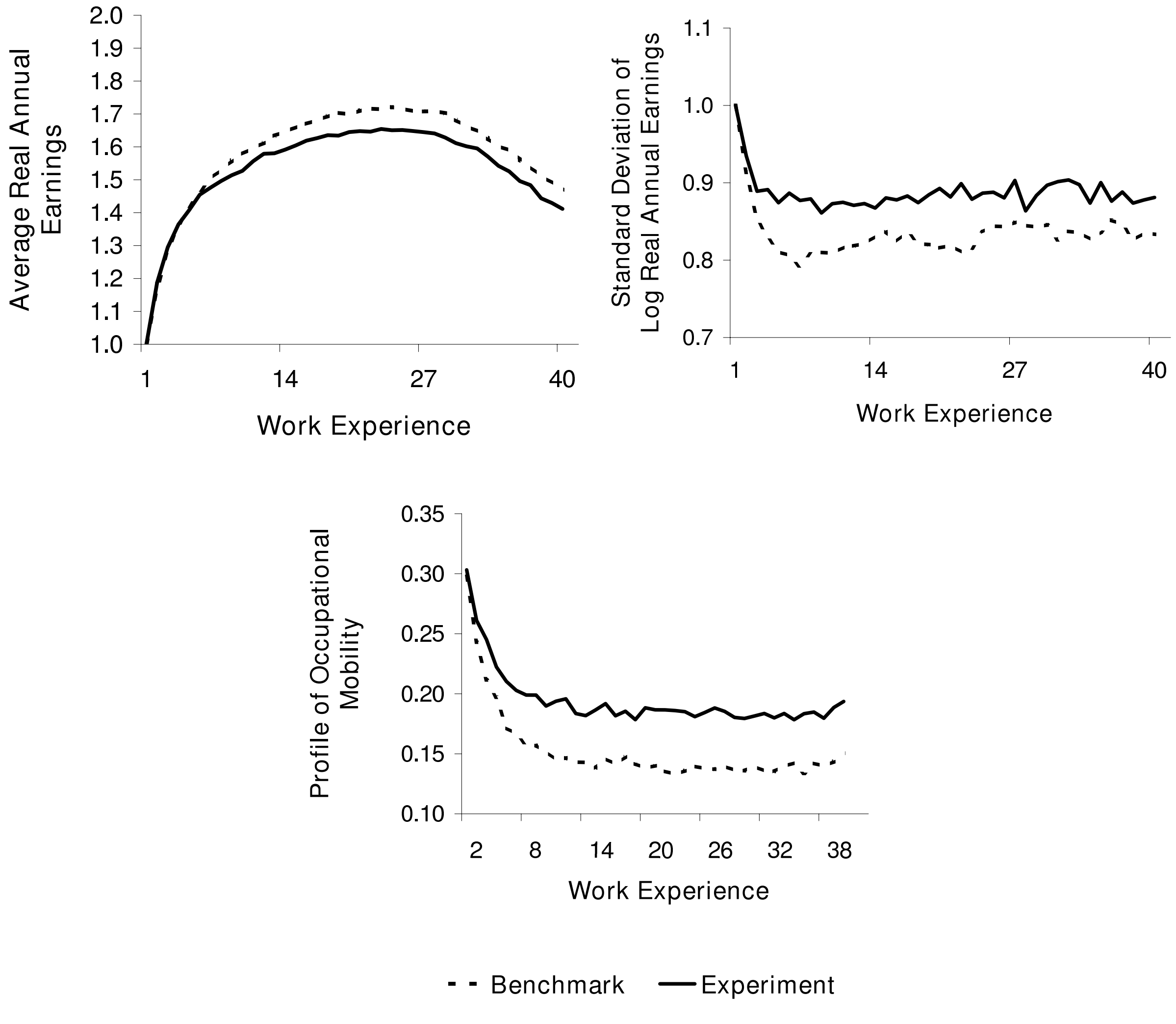


Figure 19: Sensitivity: Steady State with Higher κ.

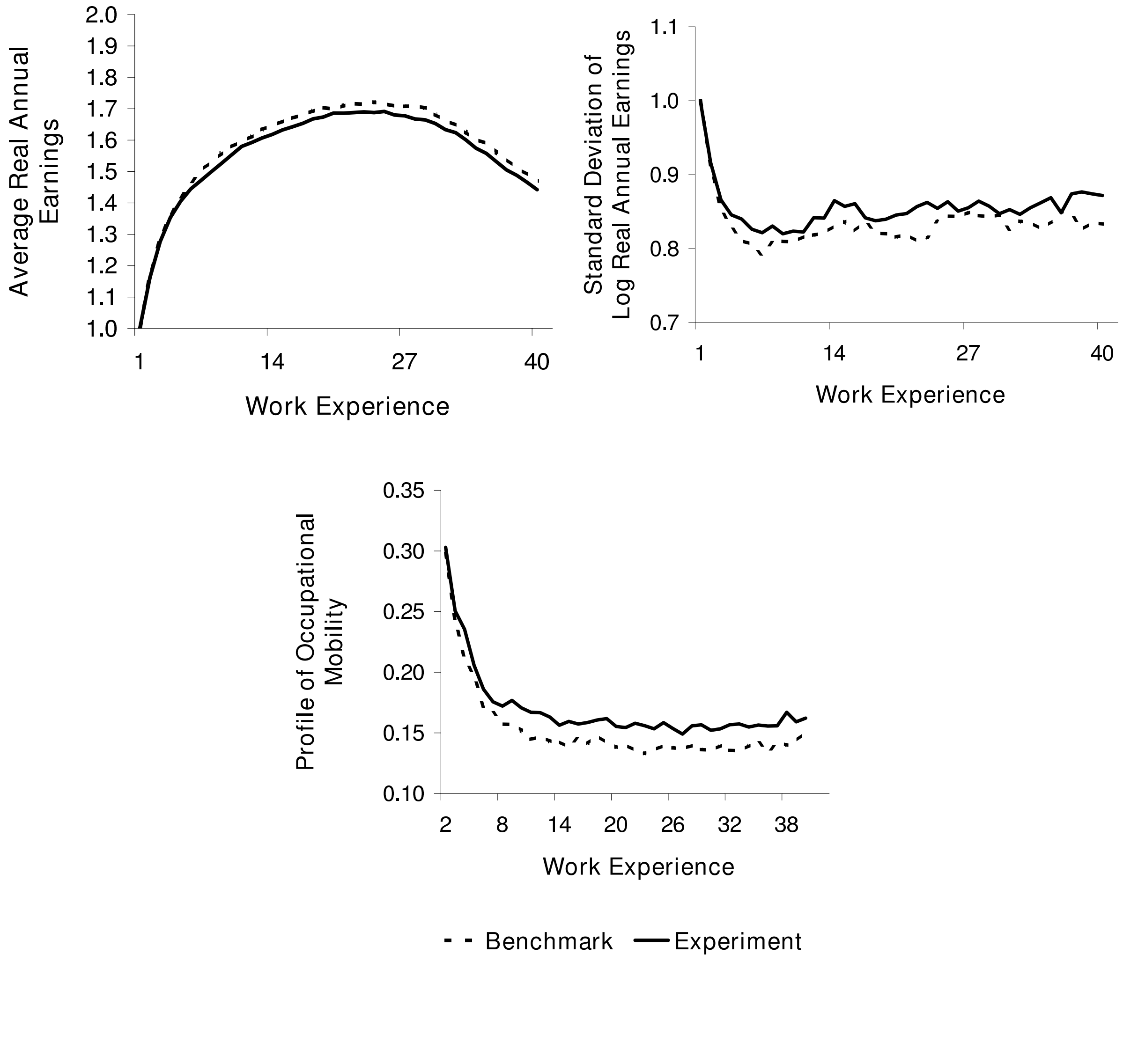


Figure 20: Sensitivity: Steady State with Higher σ_ϵ.

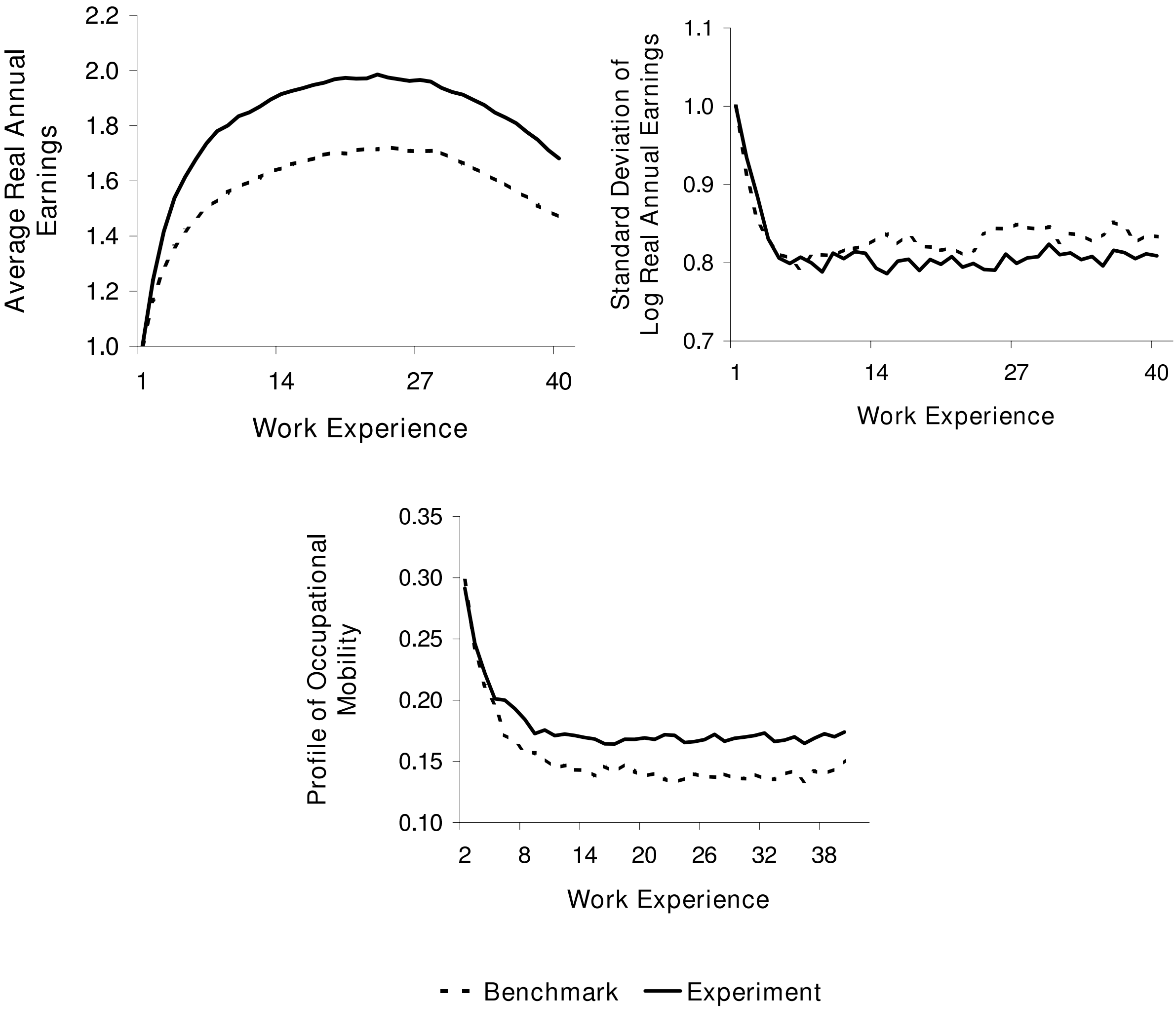


Figure 21: Sensitivity: Steady State with Lower ϕ.

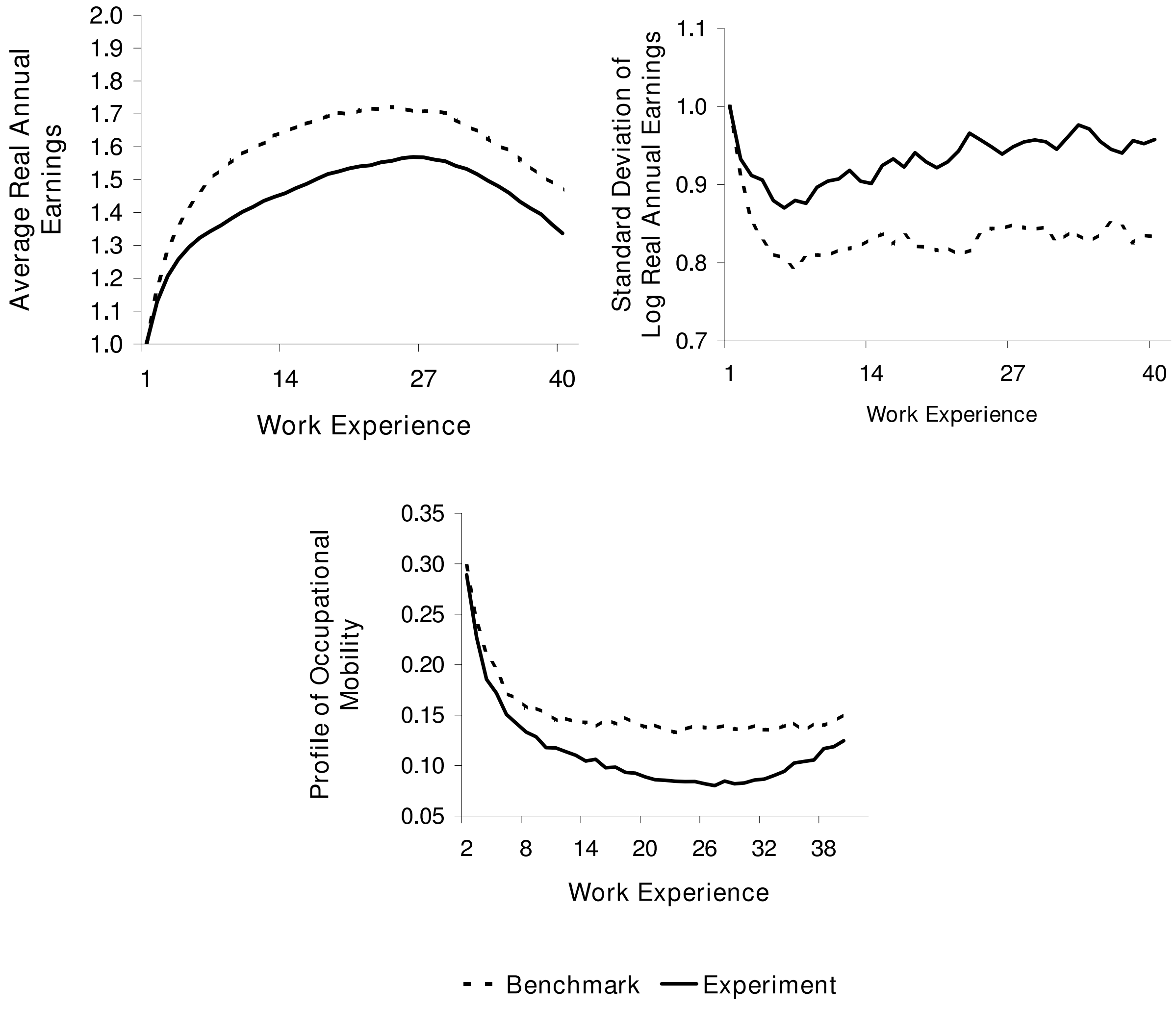


Figure 22: Sensitivity: Steady State with Lower $f_o(1)$.

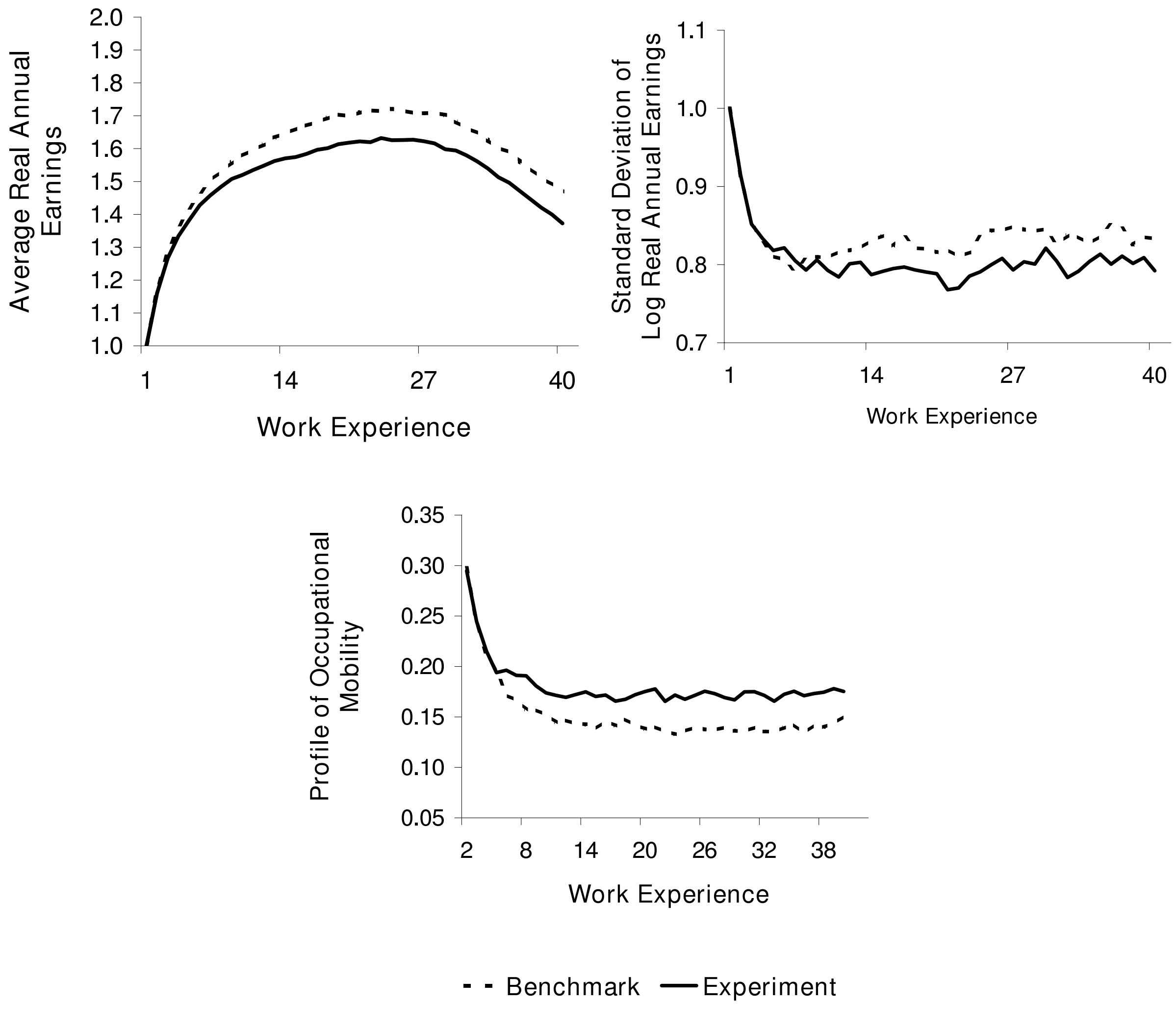


Figure 23: Sensitivity: Steady State with Lower p.

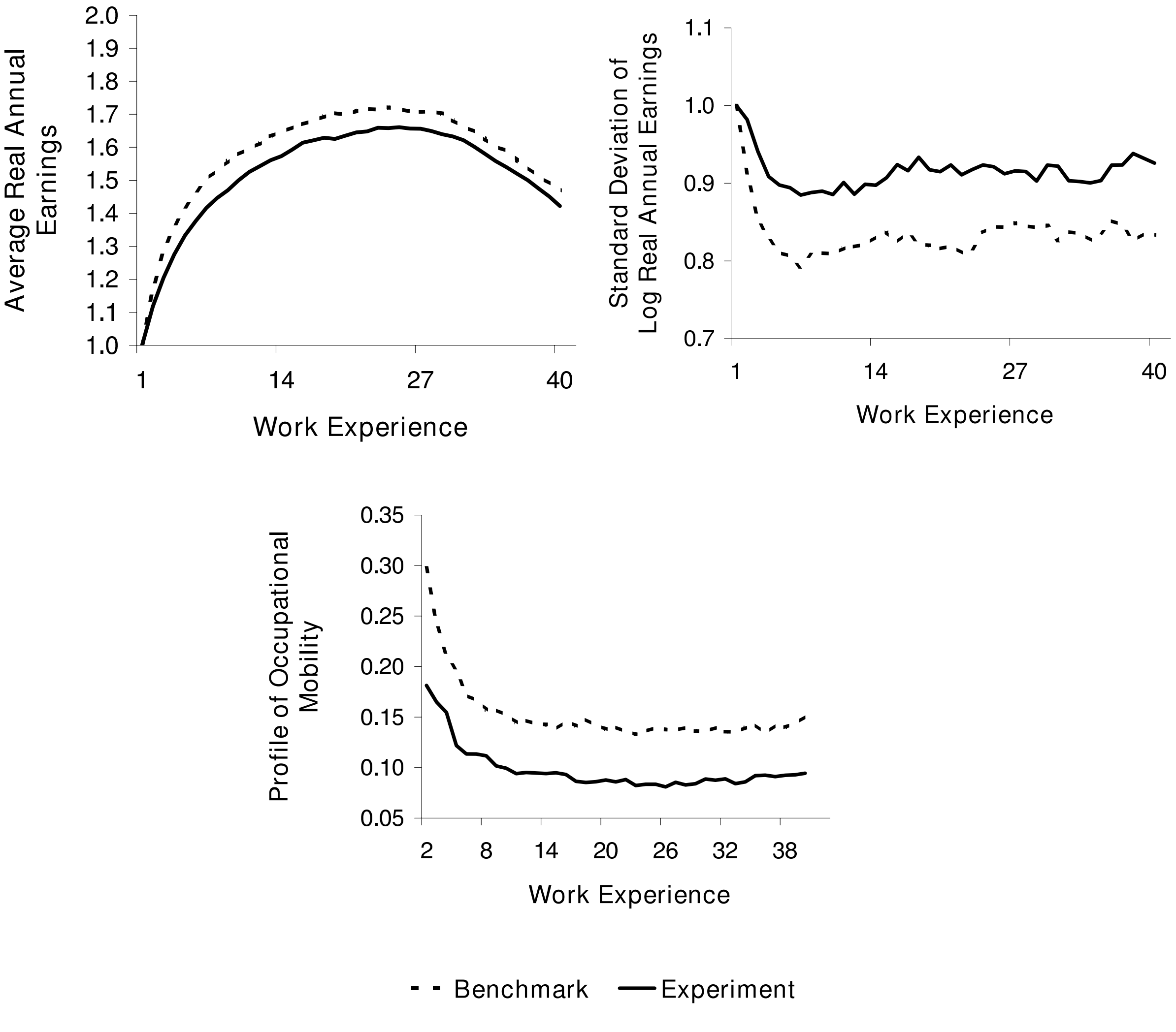
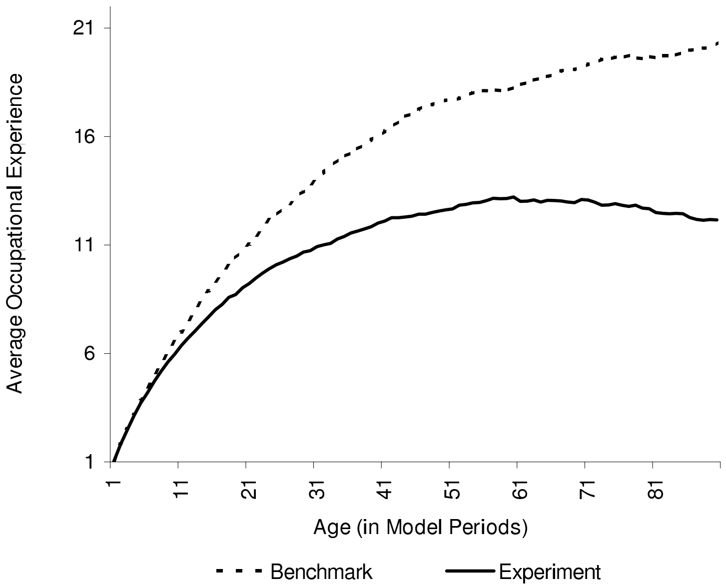


Figure 24: Life-Cycle Average Occupational Experience (in Model Periods).



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I Three-Digit Occupational Codes

PROFESSIONAL, TECHNICAL,
AND KINDRED WORKERS[14]

001 Accountants
002 Architects

Computer specialists

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

Engineers

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

Lawyers and judges

030 Judges
031 Lawyers

Librarians, archivists, and curators

032 Librarians
033 Archivists and curators

Mathematical specialists

034 Actuaries
035 Mathematicians
036 Statisticians

Life and physical scientists

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

Physicians, dentists, and related practitioners

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

Nurses, dietitians, and therapists

074 Dietitians
075 Registered nurses
076 Therapists

Health technologists and technicians

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

Religious workers

086 Clergymen
090 Religious workers, not elsewhere classified

Social scientists

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

Social and recreation workers

100 Social workers
101 Recreation workers

Teachers, college and university

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Mechanics and repairmen
470 Air conditioning, heating, and refrigeration

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

ARMED FORCES
600 Members of armed forces

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

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

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

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

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

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

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

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

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

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

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

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

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

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

II Two-Digit Occupational Codes

PROFESSIONAL, TECHNICAL
AND KINDRED WORKERS (001-195)[15]

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

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

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

CLERICAL AND KINDRED WORKERS

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

SALES WORKERS

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

CRAFTSMEN, FOREMEN,
AND KINDRED WORKERS

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

OPERATIVES AND KINDRED WORKERS

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

LABORERS

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

SERVICE WORKERS

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

FARMERS AND FARM MANAGERS

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

MISCELLANEOUS GROUPS

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

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

III One-Digit Occupational Codes

01. Professional, technical, and kindred workers (10-19)[16]
02. Managers, officials, and proprietors (20)
03. Self-employed businessmen (31)
04. Clerical and sales workers (40-45)
05. Craftsmen, foremen, and kindred workers (50-52)
06. Operatives and kindred workers (61-62)
07. Laborers and service workers, farm laborers (70-75)
08. Farmers and farm managers (80)
09. Miscellaneous (armed services, protective workers) (55)

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