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# RISING OCCUPATIONAL AND INDUSTRY MOBILITY IN THE UNITED STATES: 1968–97*

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We document and analyze the high level and the substantial increase in worker mobility in the United States over the 1968–97 period at various levels of occupational and industry aggregation. This is important in light of the recent findings that human capital of workers is largely occupation- or industry-specific. To control for measurement error in occupation and industry coding, we develop a method that utilizes the PSID Retrospective Occupation-Industry Supplemental Data Files. We emphasize the importance of our findings for understanding a number of issues such as the changes in wage inequality, aggregate productivity, job stability, and life-cycle earnings profiles.

## 1. INTRODUCTION

Neal (1995) and Parent (2000) have argued that human capital may be specific to the industry of employment (e.g., colleges and universities, trucking services, banking). More recently, Kambourov and Manovskii (2002) have documented substantial returns to occupational tenure: Everything else being constant, 5 years of occupational experience are associated with an increase in wages of at least 12%. This finding is consistent with human capital being specific to the occupation in which an individual works (e.g., truck driver, accountant, chemical engineer). Because a substantial amount of human capital may be destroyed upon switching occupation or industry, studying the levels and trends in occupational and industry mobility is important for understanding various macro and labor economic phenomena.

This article characterizes occupational and industry mobility in the United States over the 1968–97 period and contains two main messages: (1) Occupational and industry mobility in the United States is high, and (2) it has increased significantly since the late 1960s.

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For most of the analysis we use data from the Panel Study of Income Dynamics (PSID), which contains annual descriptions of occupation and industry affiliation for a panel of individuals representative of the population of the United States in each year. We define occupational mobility as the fraction of currently employed individuals who report a current occupation different from their most recent previous report of an occupation.[2] Industry mobility is defined similarly. Using these definitions, we find that among male workers over the 1968–97 period:

1. The average level of occupational mobility is around 13% at the one-digit level, 15% at the two-digit level, and 18% at the three-digit level.[3] The corresponding numbers are 10%, 11%, and 12% for industry mobility. As discussed below, these are the most reliable estimates of mobility levels in the literature.
2. Occupational mobility has increased from 10% to 15% at the one-digit level, from 12% to 17% at the two-digit level, and from 16% to 20% at the three-digit level. The corresponding increases in industry mobility are 7% to 12%, 8% to 13%, and 10% to 13%, respectively.
3. Occupational and industry mobility rates decline with worker's age and education.
4. Occupational and industry mobility has increased over time for most age–education subgroups.
5. The fact that the population has become older and more educated over the period suggests that the slowdown in the rate of increase in mobility, especially in the 1980s, may be due to demographic changes. If we reweigh the sample to keep the population structure throughout the period the same as in 1980, then we find an increase in occupational mobility from 11% to 16% at the one-digit level, from 13% to 18% at the two-digit level, and from 17% to 23% at the three-digit level.
6. Net occupational mobility, defined as one-half of the sum of the absolute changes in occupational employment shares, has increased from 1% to 3% at the one-digit level, from 3% to 6% at the two-digit level, and from 9% to over 13% at the three-digit level.
7. The increase in occupational mobility was not driven by an increased flow of workers into or out of a particular one-digit occupation.
8. Occupational mobility of government workers is relatively low and has *declined* from 10% to 6% at the two-digit level.
9. Occupational and industry switches are fairly permanent: around 30% of the workers switching occupations (industries) return to their one-digit occupation (industry) within a 4-year period after the switch whereas only 20% return to their three-digit occupation (industry) within that period.

[2] 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 in his occupation will be recorded if he reports a current occupation different from the one he reported when he was most recently employed.

[3] See Kambourov and Manovskii (2004d) for the description of the three-, two-, and one-digit occupation and industry codes.

10. Occupational mobility is mildly procyclical. Net occupational mobility is countercyclical.

These findings help shed light on four actively researched issues in macro and labor economics. In particular, we now outline the relationship between occupational mobility and the concept of economic turbulence, the job stability and job security debate, the increase in wage inequality since the early 1970s, and the flattening of life-cycle earnings profiles.

A number of researchers, following Bertola and Ichino (1995) and Ljungqvist and Sargent (1998), have described the 1970s and the 1980s as a period of increased economic turbulence. The increase in turbulence is defined as an increase in the rate of skill depreciation upon a job switch. Identifying this increase in the data, or finding other evidence of the increased turbulence, has proved elusive. Our results suggest that an observable increase in occupational mobility over the period may serve as a manifestation of the increased turbulence.

In recent years there has been substantial interest, both in the popular press and among researchers, in whether the job stability and job security of American workers has declined. Anecdotal evidence and surveys of worker perceptions suggest that stability and security declined in the 1980s and 1990s. It turned out to be difficult, however, to find a substantial increase in job (employer) mobility in the United States over the last three decades (see Journal of Labor Economics (1999) special issue). The results presented in this paper suggest that it may be appropriate to reinterpret workers' feeling of insecurity as a realization that they are now more likely to switch occupations. In addition, we find that a bigger fraction of the three-digit occupation and industry switches in the early 1990s involves a switch at the aggregated one-digit level than in the 1970s. This indicates that an occupation or industry switch in the 1990s may represent a more fundamental career change than in the 1970s.

Despite an active search by economists for the reasons behind a large increase in wage inequality among male workers in the United States over the last 30 years (an increase of 6.6 Gini points, or 25% from the late 1960s to the early 1990s), the culprit is still at large. An enormous literature has developed, mainly devoted to accounting for the rise in the college premium (e.g., Krusell et al., 2000, among many others). The increase in the college premium, however, accounts for less than a third of the overall increase in inequality. Over half of the increase was due to rising wage inequality within narrowly defined age–education subgroups of the population (e.g., Juhn et al., 1993).

Kambourov and Manovskii (2004b) suggest that a substantial part of the variance of wages for individuals from the same age–education group is accounted for by the heterogeneity of their occupational experience. Further, they show in a general equilibrium model with occupation-specific human capital that the increase in the variability of productivity (or demand) shocks to occupations from the 1960s to the 1990s, identified through the changing mobility patterns documented in this paper, accounts for over 80% of the increase in within-group wage inequality.

Knowledge of the patterns of occupational mobility elucidates the determinants of observed age-earnings profiles. It has been documented that these profiles have become flatter for each successive cohort entering the labor market during the period we study (see Kambourov and Manovskii, 2004a, for the evidence and a review of the related literature). The increase in occupational mobility, coupled with the occupational specificity of human capital, provides a possible explanation of this finding. A substantial part of the increase in the average life-cycle earnings profile is driven by an increased average occupational experience. Thus, when the average occupational experience is not rising so fast (because of more frequent occupation switches), the cohort profile of earnings is expected to be flatter.

Turning to a discussion of data issues, we note that the PSID is particularly convenient for the study of the trends in mobility over time, because it—unlike any other U.S. data set—provides consistent occupation and industry codes throughout the 1968–97 period. It is well known that panel data on occupation and industry affiliation are characterized by a substantial amount of noise. In 1999, the PSID released the Retrospective Occupation-Industry Supplemental Data Files (Retrospective Files hereafter) that recoded the reported occupations and industries for the period 1968–80. Exploiting the differences between the methodology employed by the PSID in constructing the Retrospective Files and the one employed in the original coding of the occupation and industry affiliation descriptions allows us to minimize the error in identifying true industry and occupation switches. We document that approximately 50% of occupation or industry switches identified on the uncontrolled data are not genuine and are the result of coding error. By reducing measurement error, we overcome the problem that plagued earlier attempts at identifying the levels of occupational and industry mobility.

The related literature on occupational and industry mobility is very limited. Moscarini and Vella (2003) in a recent paper have documented the behavior of occupational mobility at the three-digit level in the United States using data from the March Current Population Survey over the 1976–2000 period. Their findings are broadly consistent with ours for the overlapping period in the samples. Owing to the limitations of the March CPS, their analysis misses the biggest part of the increase in three-digit occupational mobility that took place in the first half of the 1970s. We discuss some of the relevant differences between the PSID and March CPS below.[4] In another related paper, Parrado and Wolff (1999) use the PSID and find an increase in one-digit occupational and industry mobility between the 1970s and the 1980s. Their analysis, however, is quite limited in scope and is based on the error-ridden originally coded occupation and industry affiliation data. We refer to their findings when relevant below. In an earlier work, Rosenfeld (1979) reports that occupational mobility was constant in the 1960s. This suggests that the significant increase in mobility that we find in this paper was specific to the period we study.

The article is organized as follows. In Section 2, we describe the data and document the differences between the originally coded occupation and industry affiliation data and the codes contained in the Retrospective Files. We provide evidence that the data from the Retrospective Files are more reliable. We then develop a method for controlling for measurement error that allows us to identify

[4] See Kambourov and Manovskii (2004c) for an in-depth discussion.

precise levels and trends in occupational and industry mobility over the period. This procedure, together with the patterns of mobility—overall and for various age–education subgroups of the sample—is reported in Section 3. In Section 4, we show that our findings of high and increasing mobility are robust to numerous modifications of the sample and the procedure used to control for measurement error. In Section 5, we present a number of facts that help distinguish among various theories of occupational and industry mobility. We conclude in Section 6.

## 2. THE DATA

2.1. *Sample Restrictions.* The data we use come from the PSID for the 1968–97 period.[5] The main sample consists of male heads of household, aged 23–61, who are not self- or dual-employed and are not working for the government. The resulting sample consists of 64,993 observations over the 1968–97 period, with an average of 2,166 observations a year. Restricting the sample to household heads is necessary to have occupation and industry affiliation data. This restriction does not affect our results significantly, because most workers in the PSID who satisfy our other sample selection criteria are indeed household heads. Workers younger than 23 are excluded because, in this paper, we are more interested in switches that entail human capital losses than in the early career search process. Evidence provided below, however, demonstrates that the exclusion of young workers, women, and self- or dual-employed workers does not significantly affect the results on the level and trend of aggregate mobility. The exclusion of government workers, however, is less innocuous, because occupational and industry mobility of government workers has declined substantially over the period—an issue that we discuss in depth below.

2.2. *Occupation and Industry Affiliation Data: Original vs. Retrospective Coding.* The PSID has used the 1970 Census occupation and industry codes from 1968 on. However, one-digit occupation codes were used in 1968–75, two-digit occupation codes in 1976–80, and three-digit occupation codes after 1981. The industry affiliation was coded at a two-digit level in 1971–80 and at a three-digit level after 1981.

In 1996 the PSID staff started working on the 1968–80 Retrospective Occupation-Industry Files. This work originated as part of the Working Lives and Mortality in an Aging National Cohort project. That project required three-digit occupation and industry codes throughout the course of the PSID. To produce the three-digit recode for years prior to 1981, the PSID pulled out the written records of the respondents' descriptions of their occupations and industries from its archives. These same records were the basis on which the one- and two-digit occupation and industry codes were assigned prior to 1981. Using these records, the PSID assigned three-digit 1970 Census codes to the reported occupations and industries of household heads and wives for the period 1968–80.[6] The work

[5] After 1997 the PSID switched to a new procedure in which individuals are interviewed once every two years. This makes it difficult to use the 1999 and 2001 data in studying trends and cycles in mobility.

[6] The PSID has recoded occupations and industries for most household heads and wives in the sample but not all. The analysis below is performed on weighted data. With our sample restrictions,

was completed in 1999, when the PSID released the Retrospective Occupation-Industry Supplemental Data Files.

Using the Retrospective Files, we create a series of consistent three-digit occupational codes that runs from 1968 till 1997. These codes can also be aggregated into two- and one-digit codes. Surprisingly at first, we found a significant degree of disagreement between the originally assigned PSID occupation and industry codes and the codes assigned to the same individuals in the Retrospective Files. Consider, for example, the one-digit occupational mobility for the 1969–80 period. During this period, the PSID provides the originally assigned occupation (industry) codes as well as the codes reassigned in the Retrospective Files. One would expect the levels of occupational mobility computed on these two series to be similar, if not exactly the same, because both are based on the same raw information: the respondent's description of his or her occupation contained in the PSID interview records. Any difference must come from the way the original information contained in those records was transferred into an occupation code. One finds, however, that the level of occupational mobility in the Retrospective Files during the 1969–80 period is roughly two times smaller (approximately 11%) than the mobility obtained on the originally coded occupations (approximately 22%). These two series are plotted as dotted lines in Figure 1.

Why is occupational mobility so much lower when computed using the Retrospective Files? We argue that the difference between the originally and the retrospectively assigned occupation and industry codes was caused by differences in the methodology employed by the PSID in constructing these data. When originally coding the occupation (industry) data, the PSID coder could not compare the current year description to the one in the previous year. As a result, for a respondent who is in the same occupation (industry) in both years, similar occupational (industry) descriptions could end up being coded differently. This was not the case with the constructed Retrospective Files, where, as reported in the PSID (1999), "to save time and increase reliability, the coder coded all occupations and industries for each person across all required years before moving on to the next case." Thus, in constructing the Retrospective Files, the coders had access not only to the respondents' description of their current occupation (industry) but also to the description of their past and future occupations (industries). This allowed them to compare these descriptions, decide whether they are similar, and assign the same occupational (industry) code where appropriate.

Our hypothesis is supported by the results of an experiment summarized in Mathiowetz (1992). Reports of occupations obtained in interviews of employees of a large company were checked against company records. This was done in two ways. First, the coders were asked to compare simultaneously the two descriptions and to code them as being in agreement if the two sources could result in the same three-digit classification. The procedure resulted in a disagreement rate of 12.7%. Second, the coders independently coded the two descriptions at the one- and

among individuals who appear more than twice in the sample, only 82 observations with positive PSID sample weights were not recoded. These nonrecoded observations do not exhibit a trend over time and have virtually no impact on the average sample characteristics.


FIGURE 1

OCCUPATIONAL MOBILITY, ONE DIGIT LEVEL, RETROSPECTIVE AND ORIGINAL PSID FILES, 1969–80 .

NOTES: THE DOTTED LINES SHOW THE ACTUAL LEVEL OF OCCUPATIONAL MOBILITY—THE HIGHER ONE IS COMPUTED ON THE ORIGINALLY CODED DATA WHEREAS THE LOWER ONE IS COMPUTED ON THE RETROSPECTIVE FILES. THE SOLID LINES SHOW THE ESTIMATED TREND IN OCCUPATIONAL MOBILITY FROM A LINEAR PROBABILITY MODEL—THE HIGHER ONE IS COMPUTED ON THE ORIGINALLY CODED DATA WHEREAS THE LOWER ONE IS COMPUTED ON THE RETROSPECTIVE FILES

three-digit levels. The comparison of the independently assigned codes resulted in a disagreement rate of 48.2% at the three-digit level and 24.3% at the one-digit level. The results indicate that by far the largest amount of error in occupational or industry affiliation data is generated at the coding stage.[7]

The discussion above suggests that the occupation and industry codes from the Retrospective Files are more reliable and that there is a higher degree of misclassification of occupations and industries in the originally coded data. Kambourov and Manovskii (2002) show that the Retrospective Files are indeed much more reliable than the originally coded data.

## 3. OCCUPATIONAL AND INDUSTRY MOBILITY IN THE UNITED STATES

This section contains the main result of the paper. In particular, we document the levels and trends in occupational and industry mobility in the United States using the data from the Retrospective Files for the 1968–80 period and the originally coded data for the 1981–97 period. The use of the Retrospective Files allows us to minimize the measurement error in occupation and industry coding.

[7] In a related paper Mellow and Sider (1983) find that a direct comparison of independently coded individual responses to the CPS with employer records yielded an agreement rate of only 92.3% and 81% for one-digit industries and occupations, respectively, and 84.1% and 57.6% for three-digit industries and occupations, respectively.

3.1. *Methodology.* As discussed above, the level of occupational mobility after 1981 obtained from the originally coded data is substantially higher than the one before 1980 obtained from the Retrospective Files. As is suggested by Figure 1, the presence of coding error in the originally coded dat a causes an affine shift in the plot of mobility relative to that obtained on the Retrospective Files (we test this formally below in Section 4.2). Thus, to control for the effects of the change in the coding procedure in 1981, we adopt the following procedure.

We divide the sample into 26 age–education categories. By age, individuals are divided into 13 three-year age groups, starting with age 23. Thus, the variable *Age* that we use below takes values from 1 to 13. By education, individuals are divided into those who have 12 years of education or less and those who have more than 12 years of education.[8] We postulate the following model:

$$P_{it} \equiv Pr(y_{it} = 1|X_{it}) = E(y_{it}|X_{it}) = \xi(X_{it}\beta), \tag{1}$$

where

$$\begin{aligned} X_{it}\beta = \beta_0 &+ \beta_1 Age + \beta_2 Age^2 + \beta_3 Time + \beta_4 Unemp + \beta_5 Break \\ &+\beta_6 Time * Age + \beta_7 Unemp * Age + \beta_8 Break * Age \\ &+\beta_9 Time * Age^2 + \beta_{10} Unemp * Age^2 + \beta_{11} Break * Age^2. \end{aligned} \tag{2}$$

In this specification, $y_{it}$ is a binary variable that assumes the value of one if individual $i$ switches her, say, occupation in period $t$ and is zero otherwise. Our analysis will be based on the probit specification $E(y_{it} \mid X_{it}) = \Phi(X_{it}\beta)$, where $\Phi(\cdot)$ represents the cumulative standard normal distribution function, as well as a linear probability model that postulates $E(y_{it} \mid X_{it}) = X_{it}\beta$. We model an individual's occupational or industry switch to depend on her age, age squared, a time trend, and the current level of unemployment in the county of residence. Because of the change in the coding procedure in 1981, we also include a dummy variable *Break*, which assumes the value of one if the year is in the period 1981–97. Further, we interact the time trend, the unemployment variable, and the break variable with age and age squared in order to allow different age groups to have different trends in mobility over time and over the business cycle, as well as different changes in mobility as a result of the change in the coding procedure in 1981. Finally, all of the above variables are interacted with an education dummy variable that takes the value of one if the individual has more than 12 years of education and zero otherwise. The complete list of variables is contained in Table 1.[9] The model is

[8] We do not use a finer age–education partition, because this would lead to some groups having too small sizes in some years.

[9] We allow for the interactions between dummy variable *Break*, age, and education because one may expect the coding error to be distributed nonuniformly over age–education groups. This may be particularly true at the three-digit level, since, at this level, occupations are very disaggregated and although it is virtually impossible to misclassify a medical doctor, it is possible to misclassify a machine operator, and the distribution of doctors and machine operators is not uniform across the age–education groups. On the one- and two-digit level occupational classifications, however, one has less reason to expect the coding error to vary across the age–education groups. Similar arguments apply to industries.

TABLE 1
ESTIMATION RESULTS

| Variable | Occupation 1-Digit (1) | Occupation 2-Digit (2) | Occupation 3-Digit (3) | Industry 1-Digit (4) | Industry 2-Digit (5) | Industry 3-Digit (6) |
|---|---|---|---|---|---|---|
| Age | −0.0135 | −0.0194 | −0.0311 | −0.0183 | −0.0304 | −0.0328 |
| | (0.0115) | (0.0122) | (0.0140) | (0.0103) | (0.0112) | (0.0132) |
| Agesq | −0.0006 | −0.0001 | 0.0004 | 0.0002 | 0.0010 | 0.0009 |
| | (0.0009) | (0.0009) | (0.0010) | (0.0008) | (0.0009) | (0.0010) |
| Time | 0.0034 | 0.0038 | 0.0062 | 0.0052 | 0.0058 | 0.0051 |
| | (0.0021) | (0.0022) | (0.0026) | (0.0018) | (0.0021) | (0.0024) |
| Break | 0.0094 | 0.0221 | 0.0699 | −0.0048 | 0.0108 | 0.0819 |
| | (0.0329) | (0.0352) | (0.0407) | (0.0292) | (0.0330) | (0.0362) |
| U | 0.0094 | 0.0110 | 0.0126 | 0.0060 | 0.0084 | 0.0104 |
| | (0.0035) | (0.0037) | (0.0043) | (0.0029) | (0.0034) | (0.0040) |
| Time∗Age | −0.0004 | −0.0001 | −0.0007 | −0.0010 | −0.0009 | −0.0012 |
| | (0.0008) | (0.0008) | (0.0010) | (0.0007) | (0.0008) | (0.0009) |
| Time∗Agesq∗100 | 0.0023 | −0.0022 | 0.0009 | 0.0061 | 0.0034 | 0.0065 |
| | (0.0058) | (0.0058) | (0.0071) | (0.0051) | (0.0058) | (0.0065) |
| U∗Age | −0.0052 | −0.0057 | −0.0060 | −0.0024 | −0.0030 | −0.0035 |
| | (0.0013) | (0.0014) | (0.0016) | (0.0012) | (0.0013) | (0.0015) |
| U∗Agesq | 0.0004 | 0.0004 | 0.0004 | 0.0002 | 0.0002 | 0.0002 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| Break∗Age | 0.0292 | 0.0232 | 0.0363 | 0.0277 | 0.0360 | 0.0505 |
| | (0.0129) | (0.0138) | (0.0159) | (0.0114) | (0.0129) | (0.0147) |
| Break∗Agesq | −0.0013 | −0.0006 | −0.0010 | −0.0012 | −0.0012 | −0.0021 |
| | (0.0010) | (0.0010) | (0.0012) | (0.0009) | (0.0010) | (0.0011) |
| Educ | 0.0419 | 0.0909 | −0.0346 | 0.0339 | 0.0097 | 0.0247 |
| | (0.0544) | (0.0584) | (0.0657) | (0.0481) | (0.0540) | (0.0619) |
| Educ∗Age | −0.0505 | −0.0574 | −0.0241 | −0.0214 | −0.0164 | −0.0307 |
| | (0.0201) | (0.0214) | (0.0245) | (0.0182) | (0.0205) | (0.0232) |
| Educ∗Agesq | 0.0036 | 0.0037 | 0.0020 | 0.0008 | 0.0008 | 0.0019 |
| | (0.0015) | (0.0016) | (0.0019) | (0.0014) | (0.0016) | (0.0018) |
| Educ∗Time | 0.0003 | −0.0004 | 0.0026 | −0.0017 | −0.0011 | −0.0010 |
| | (0.0034) | (0.0037) | (0.0043) | (0.0030) | (0.0034) | (0.0039) |
| Educ∗Break | −0.0550 | −0.0701 | −0.0937 | 0.0130 | 0.0216 | 0.0131 |
| | (0.0519) | (0.0552) | (0.0658) | (0.0503) | (0.0577) | (0.0649) |

TABLE 1
(CONTINUED)

| Variable | Occupation 1-Digit (1) | Occupation 2-Digit (2) | Occupation 3-Digit (3) | Industry 1-Digit (4) | Industry 2-Digit (5) | Industry 3-Digit (6) |
|---|---|---|---|---|---|---|
| Educ∗U | −0.0071 | −0.0107 | −0.0001 | −0.0013 | −0.0028 | −0.0050 |
| | (0.0062) | (0.0066) | (0.0077) | (0.0053) | (0.0062) | (0.0070) |
| Educ∗Time∗Age | 0.0002 | −0.0004 | −0.0015 | 0.0009 | 0.0003 | 0.0008 |
| | (0.0013) | (0.0013) | (0.0015) | (0.0011) | (0.0012) | (0.0014) |
| Educ∗Time∗ Agesq∗100 | 0.0011 | 0.0078 | 0.0125 | −0.0037 | 0.0001 | −0.0044 |
| | (0.0095) | (0.0101) | (0.0112) | (0.0085) | (0.0093) | (0.0106) |
| Educ∗U∗Age | 0.0041 | 0.0048 | 0.0015 | 0.0004 | 0.0014 | 0.0025 |
| | (0.0023) | (0.0025) | (0.0028) | (0.0021) | (0.0023) | (0.0026) |
| Educ∗U∗Agesq | −0.0003 | −0.0003 | −0.0001 | 0.0001 | −0.0001 | −0.0002 |
| | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) |
| Educ∗Break∗Age | 0.0269 | 0.0472 | 0.0659 | 0.0036 | 0.0017 | −0.0024 |
| | (0.0215) | (0.0229) | (0.0265) | (0.0193) | (0.0217) | (0.0245) |
| Educ∗Break ∗Agesq | −0.0020 | −0.0038 | −0.0047 | −0.0006 | −0.0003 | −0.0001 |
| | (0.0016) | (0.0017) | (0.0020) | (0.0015) | (0.0016) | (0.0018) |
| *N* of Obs. | 42864 | 42864 | 42864 | 42747 | 42747 | 42747 |

NOTES: The results are from a probit regression in which the dependent variable is whether there was a corresponding switch or not. In the case of continuous variables, the reported coefficients show the change in the probability of a switch as a result of a marginal increase in the variable around its mean. In the case of dummy variables, the reported coefficients tell us the change in the probability of a switch when the dummy variable changes from 0 to 1. Standard errors are in parentheses.

estimated on our full sample. Finally, because we assume that the coding error present in our data results only in an affine shift in the argument of $\xi$, all the data (i.e., the data before and after 1980) identify the time trend.

The estimated coefficients allow us to obtain fitted values for each individual—the predicted probability of an occupation (industry) switch—in each of the years that the individual is in the sample. We predict one's mobility in each year after 1980 if there was no structural change in the coding procedure (setting the coefficient on *Break* and all of its interactions to zero). Using these fitted values, we obtain occupational (industry) mobility—overall and in each of the age–education groups. The difference between the predicted probability of a switch in each year with and without setting the coefficient on *Break* to zero represents the estimate of mobility due to the coding error. When plotting the aggregate occupational and industry mobility (not the fitted lines) in Figures 2, 3, and 6, we subtract the estimate of mobility due to the coding

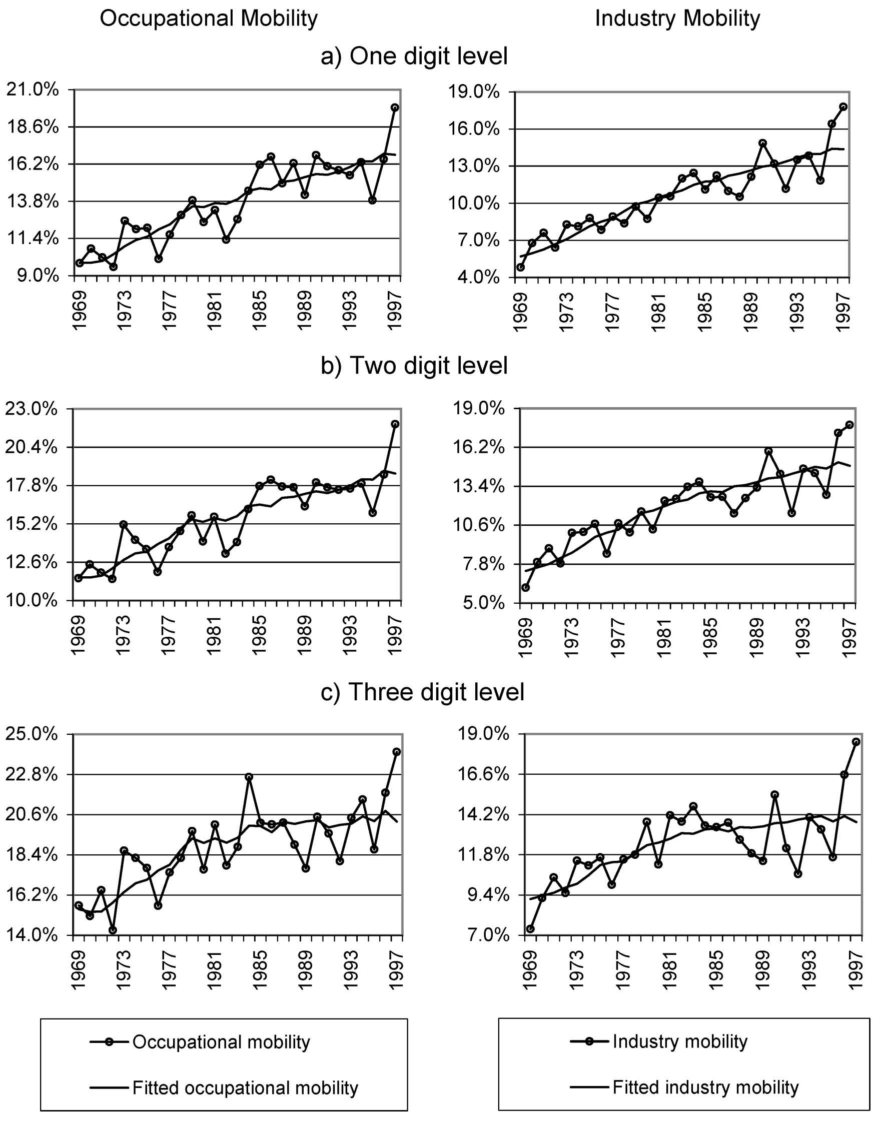


FIGURE 2

OCCUPATIONAL AND INDUSTRY MOBILITY IN THE UNITED STATES, 1969–97, LINEAR PROBABILITY MODEL

error from the raw data in each year after 1980. Our estimates imply that the use of the uncontrolled data will result in estimates of the three-digit occupational and industry mobility that is approximately 25 percentage points higher than its true level. The estimate of mobility due to the coding error goes down but is still substantial at 14 and 10 percentage points at the two- and one-digit levels, respectively.

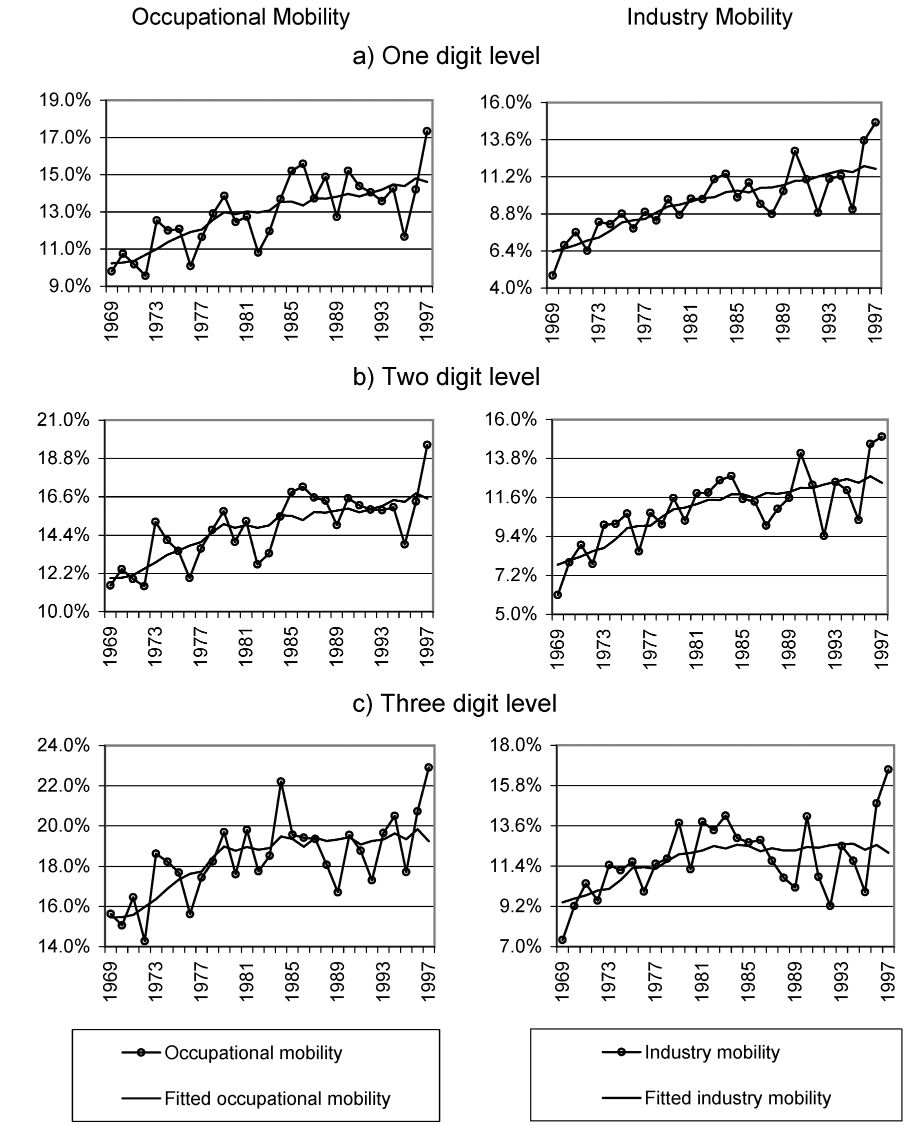


FIGURE 3

OCCUPATIONAL AND INDUSTRY MOBILITY IN THE UNITED STATES, 1969–97, PROBIT REGRESSION

We weigh the sample using the PSID sample weights that make the sample representative of the U.S. population in each period. This weighing has little effect on our results.

A useful additional experiment is to consider mobility trends had the overall age, educational, and racial structure of the population remained constant throughout the 1968–97 period. To this end, we divide the sample into 88 age–education–race groups.[10] We then construct 1970 weights, 1980 weights, 1990 weights, as well as average weights that reflect the average size of each group during the period. For example, in constructing the 1980 weights, we calculate the relative size of each group in 1980. Then, in all other years, we scale everyone's weight in each group in order to keep the relative size of each group at its 1980 level. Weighing the sample using, say, the 1970 weights will then be suggestive of the behavior of occupational and industry mobility in the United States had its population not grown older and more educated on the average. In this sense, fixing the population structure may provide a better picture of the underlying changes in the forces affecting the labor markets. This experiment is, of course, based on a strong assumption that changing demographics does not affect the switching behavior of each worker.

3.2. *Main Results.* Figure 2 plots the estimates of mobility across occupations and industries over the 1968–97 period obtained from a linear probability version of Equation (1). Figure 3 depicts the corresponding estimates of mobility obtained from the probit version of Equation (1). Table 1 reports the estimation results from the probit model for occupation and industry switches. Figures 4 and 5 plot the estimated trends in occupational and industry mobility by age and education groups. Finally, Figure 6 depicts the estimates of mobility across occupations and industries over the 1968–97 period obtained from the probit version of Equation (1) for the fixed 1980 population structure.

3.2.1. *The level of overall mobility.* As summarized in Table 2, the average level of occupational mobility is 13% at the one-digit level, 15% at the two-digit level, and 18% at the three-digit level. The corresponding numbers are 10%, 11%, and 12% for industry mobility. As illustrated below, despite being apparently high, these estimates of the level of mobility are substantially lower than the ones obtained from the originally coded data (e.g., Parrado and Wolff, 1999). In fact, because we use the Retrospective Files in the analysis, these numbers represent the most accurate estimates of the annual occupational mobility in the literature.

The numbers above suggest that the one-, two-, and three-digit mobility levels are of a similar enough magnitude so that many of the switches at a three-digit level are also switches across the much more aggregated one- and two-digit codes (a switch at a one-digit level implies a switch at the two- and three-digit levels, but not otherwise). For example, consistent with Markey and Parks (1989), we find that almost 70% of the three-digit occupational switches entail a one-digit occupational switch. It is notable that the fraction of three-digit switches that are also one- or two-digit switches has increased significantly over the period.

3.2.2. *Dynamics of overall mobility.* All of the panels in Figures 2 and 3 exhibit an increase in overall occupational and industry mobility over the period. For

[10] Specifically, by age, individuals are divided into 11 four-year age groups, starting with age 22. By education, individuals are divided into high-school dropouts, high-school graduates, some college, and college graduates. By race, individuals are divided into whites and nonwhites.

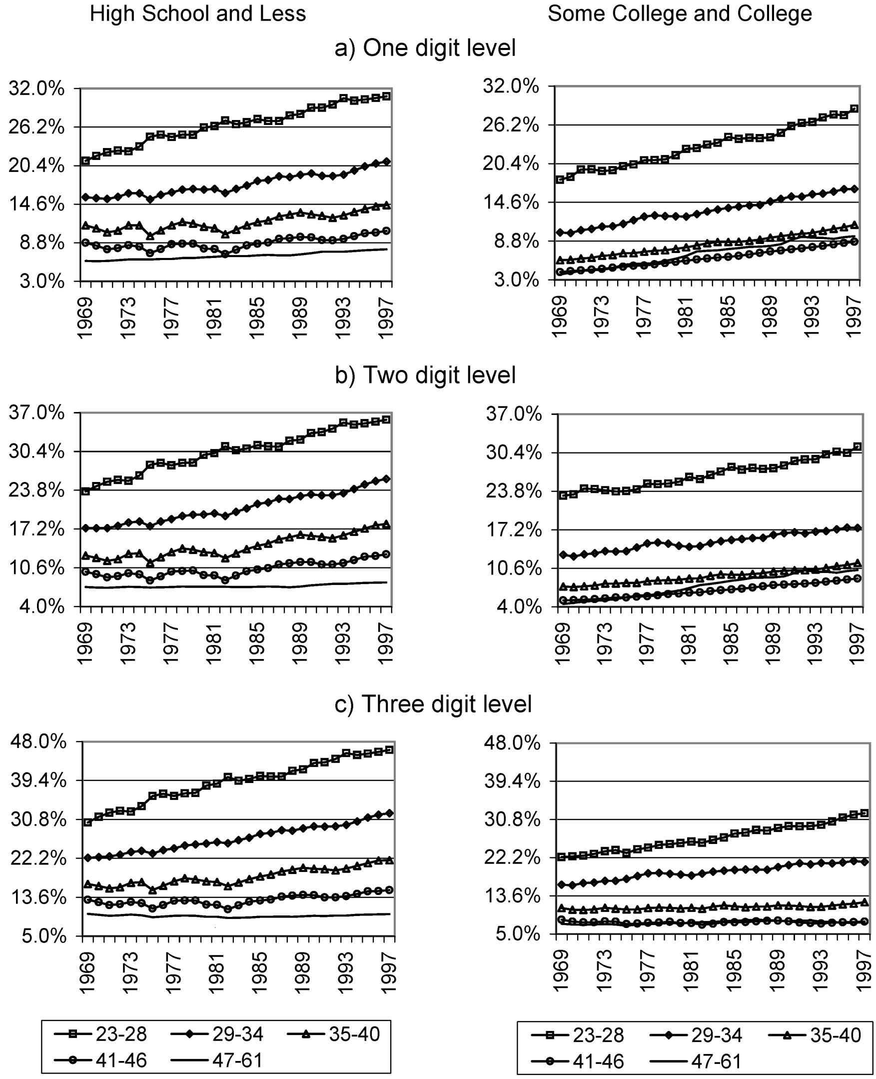


FIGURE 4

OCCUPATIONAL MOBILITY IN THE UNITED STATES BY AGE AND EDUCATION LEVELS, 1969–97

example, under the more conservative probit regression, occupational mobility has increased from 10% to 15% at the one-digit level, from 12% to 17% at the two-digit level, and from 16% to 20% at the three-digit level. The estimates of the time trend of overall mobility also obtained from the probit regression are presented in Table 3. The reported coefficients represent the derivative of the probit function with respect to time. For the overall sample results, the derivative is computed around the mean of all variables. All of the reported increases in mobility are

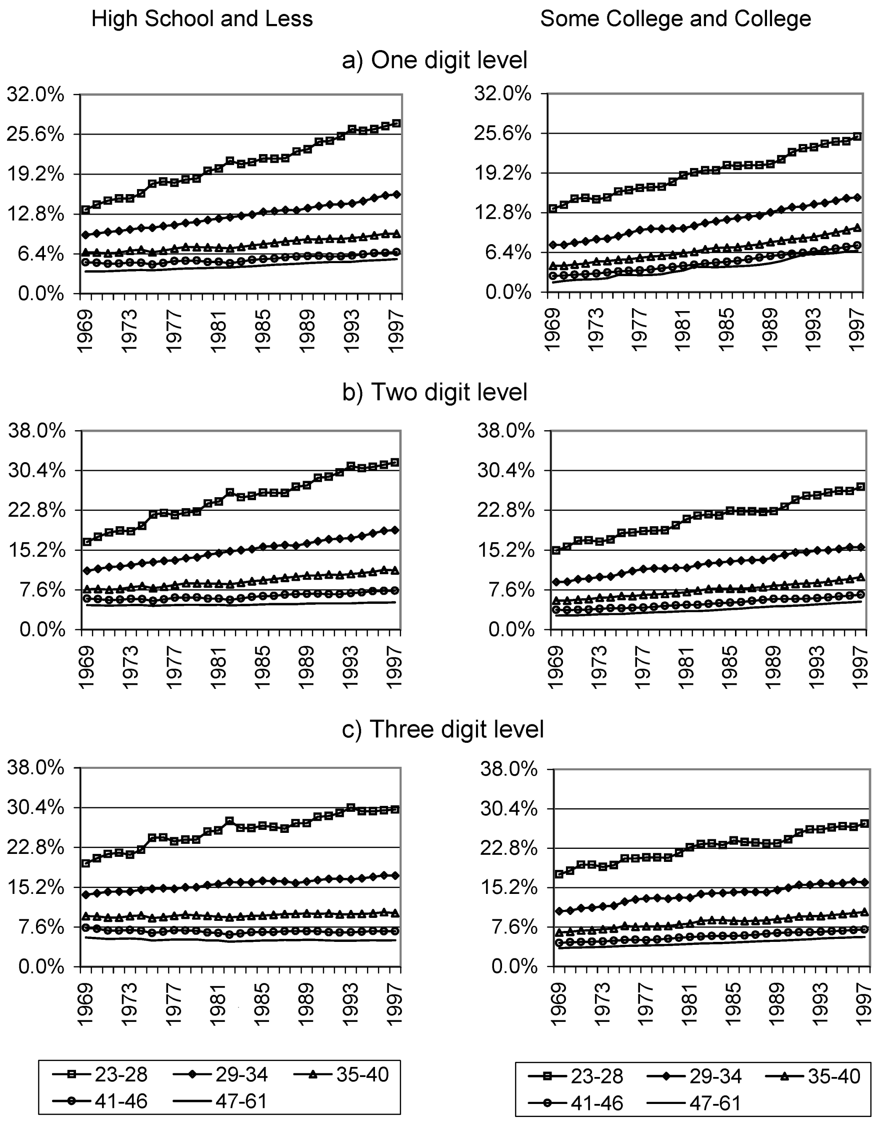


FIGURE 5

INDUSTRY MOBILITY IN THE UNITED STATES BY AGE AND EDUCATION LEVELS, 1969–97

statistically significant at the 1% level. The trend in three-digit occupational mobility that we identify is consistent with the findings in Markey and Parks (1989) based on the January CPS supplements collected periodically since 1966.[11]

[11] Murphy and Topel (1987) have argued using the March CPS data that two-digit industry mobility has declined sharply over the 1970–84 period. Their result is entirely driven by a 40% decline in

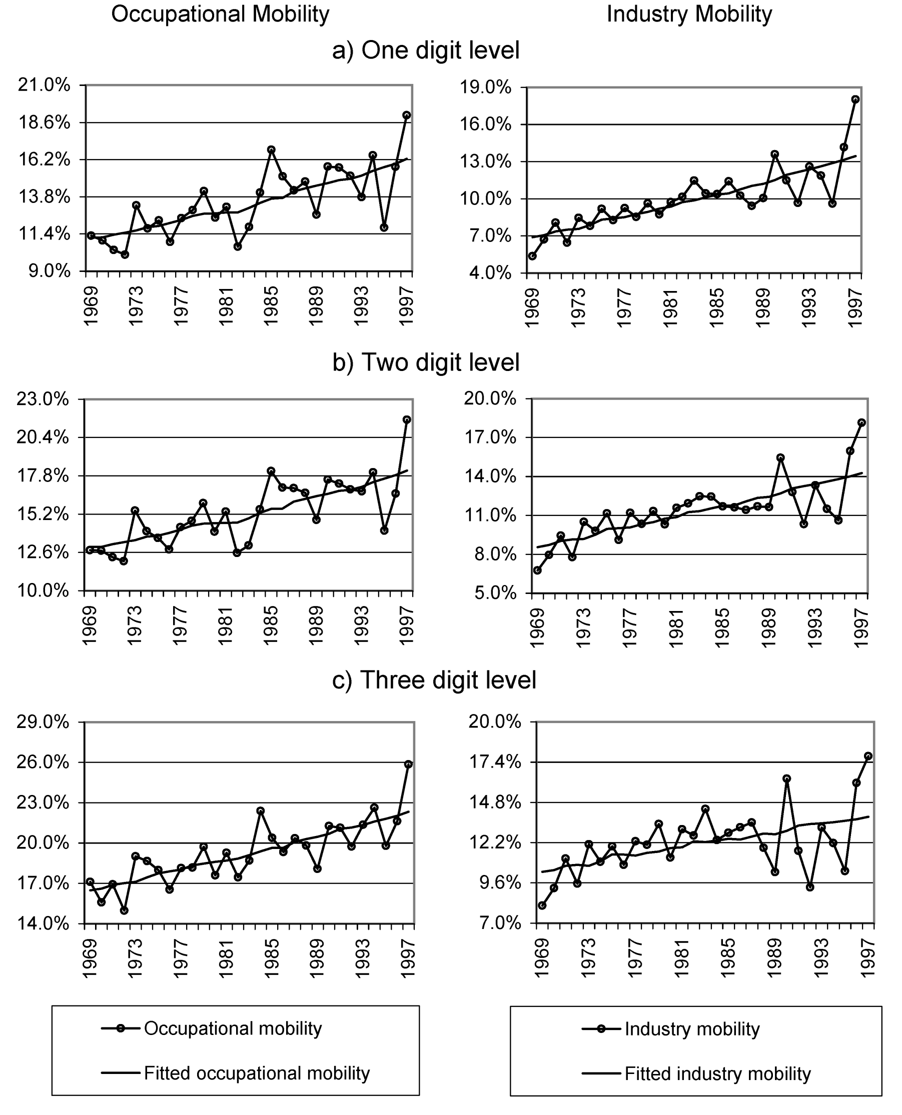


FIGURE 6

OCCUPATIONAL AND INDUSTRY MOBILITY IN THE UNITED STATES, 1969–97, PROBIT REGRESSION, CONSTANT 1980 POPULATION STRUCTURE

This rise in mobility may imply a substantial increase in the destruction rate of human capital.

mobility between 1975 and 1976. Moscarini and Vella (2003) argue that this was due to a revision in the March CPS imputation procedures in 1976. There is no evidence of this decline in either the PSID or the January CPS data. See Kambourov and Manovskii (2004c) for a cautionary discussion of the use of the March CPS to study worker mobility.

TABLE 2

AVERAGE ESTIMATED SWITCH PROBABILITY: OVERALL AND BY AGE–EDUCATION GROUPS

| | Occupation | | | Industry | | |
|---|---|---|---|---|---|---|
| Age | 1-Digit (1) | 2-Digit (2) | 3-Digit (3) | 1-Digit (4) | 2-Digit (5) | 3-Digit (6) |
| | | | **A. Overall** | | | |
| 23–61 | 0.1300 | 0.1490 | 0.1848 | 0.0973 | 0.1109 | 0.1182 |
| | (0.0003) | (0.0004) | (0.0005) | (0.0003) | (0.0004) | (0.0004) |
| | | | **B. Some College and College** | | | |
| 23–28 | 0.2301 | 0.2665 | 0.3355 | 0.1920 | 0.2133 | 0.2294 |
| | (0.0008) | (0.0009) | (0.0013) | (0.0008) | (0.0008) | (0.0008) |
| 29–34 | 0.1376 | 0.1547 | 0.1932 | 0.1176 | 0.1299 | 0.1419 |
| | (0.0004) | (0.0004) | (0.0005) | (0.0004) | (0.0004) | (0.0004) |
| 35–40 | 0.0888 | 0.0963 | 0.1118 | 0.0752 | 0.0802 | 0.0892 |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0003) |
| 41–46 | 0.0690 | 0.0733 | 0.0764 | 0.0545 | 0.0546 | 0.0617 |
| | (0.0003) | (0.0003) | (0.0001) | (0.0003) | (0.0002) | (0.0002) |
| 47–61 | 0.0725 | 0.0797 | 0.0759 | 0.0424 | 0.0400 | 0.0468 |
| | (0.0004) | (0.0005) | (0.0003) | (0.0003) | (0.0002) | (0.0001) |
| | | | **C. High School and Less** | | | |
| 23–28 | 0.2654 | 0.3040 | 0.3909 | 0.2073 | 0.2501 | 0.2601 |
| | (0.0005) | (0.0006) | (0.0008) | (0.0006) | (0.0007) | (0.0006) |
| 29–34 | 0.1782 | 0.2113 | 0.2707 | 0.1276 | 0.1538 | 0.1592 |
| | (0.0003) | (0.0004) | (0.0005) | (0.0003) | (0.0004) | (0.0003) |
| 35–40 | 0.1215 | 0.1463 | 0.1846 | 0.0803 | 0.0952 | 0.0988 |
| | (0.0003) | (0.0004) | (0.0004) | (0.0002) | (0.0002) | (0.0002) |
| 41–46 | 0.0880 | 0.1043 | 0.1307 | 0.0551 | 0.0636 | 0.0679 |
| | (0.0002) | (0.0003) | (0.0003) | (0.0001) | (0.0001) | (0.0001) |
| 47–61 | 0.0672 | 0.0746 | 0.0947 | 0.0431 | 0.0480 | 0.0514 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |

NOTES: Each cell represents the average, over the 1969–1997 period, predicted probability of a switch for the overall sample and for a given age–education group. Standard errors are in parentheses.

3.2.3. *Patterns of mobility for various age–education groups.* Figures 4 and 5 and Tables 2 and 3 summarize the patterns of mobility across occupations and industries over the 1969–97 period for various age–education groups.

As might be expected, levels of mobility differ significantly across the age–education groups. Both occupational and industry mobility rates decline with age.[12] This finding is consistent with the standard human capital and occupational-matching theories and is corroborated by the evidence in Miller (1984) and McCall

[12] Because levels of mobility on one-, two-, and three-digit level are close to each other, and because the statistical model we have estimated did not impose any restrictions on estimates at different aggregation levels, it is possible that the estimated levels of mobility do not increase monotonically with

TABLE 3

TIME TREND IN MOBILITY: OVERALL AND BY AGE–EDUCATION GROUPS

| | Occupation | | | Industry | | |
|---|---|---|---|---|---|---|
| Age | 1-Digit (1) | 2-Digit (2) | 3-Digit (3) | 1-Digit (4) | 2-Digit (5) | 3-Digit (6) |
| **A. Overall** | | | | | | |
| 23–61 | .0026*** | .0026*** | .0023*** | .0030*** | .0026*** | .0017*** |
| **B. Some College and College** | | | | | | |
| 23–28 | .0040** | .0033* | .0062*** | .0047*** | .0049*** | .0041** |
| 29–34 | .0034*** | .0026** | .0029** | .0041*** | .0037*** | .0034*** |
| 35–40 | .0032*** | .0025** | .0008 | .0039*** | .0030*** | .0028** |
| 41–46 | .0033*** | .0029** | −.0001 | .0037*** | .0026** | .0024* |
| 47–61 | .0039*** | .0041*** | .0007 | .0035*** | .0024** | .0021 |
| **C. High School and Less** | | | | | | |
| 23–28 | .0036** | .0045*** | .0058*** | .0052*** | .0058*** | .0041** |
| 29–34 | .0025*** | .0037*** | .0043*** | .0030*** | .0037*** | .0019* |
| 35–40 | .0017* | .0027*** | .0028** | .0016* | .0021** | .0004 |
| 41–46 | .0012 | .0017* | .0015 | .0010 | .0010 | −.0003 |
| 47–61 | .0010 | .0004 | .0000 | .0013 | .0004 | −.0003 |

NOTES: The results are from a probit regression in which the dependent variable is whether there was a corresponding switch or not. The reported coefficients represent the derivative of the probit function with respect to time. For the overall sample results, the derivative is computed around the mean of all variables. For the various age–education groups, the derivative is computed around the variables' means for that particular group. ***—statistically significant at 1%, **—statistically significant at 5%, *—statistically significant at 10%.

(1990). If human capital of workers is accumulated with occupational experience, the opportunity cost of switching occupations is rising with occupational tenure.[13] Thus, as the average occupational experience in a cross section of workers is rising with age, occupational mobility is declining with age. In addition, life-cycle considerations reduce mobility with age, because the pay-off period from investing in skills in the new occupation or learning about the match quality with the new occupation declines with age.[14]

In the same age group, the college-educated workers exhibit lower occupational mobility than their less educated counterparts. This is perhaps not surprising. Because college education may be thought of as representing investment in human capital that is not perfectly transferable across all occupations, it is expected to reduce workers' occupational mobility. What is surprising, however, is the finding that occupational mobility of college-educated workers is quite high. This indicates that either college provides workers with skills that are fairly transferable (general) or that college education represents a very risky investment for workers. Both possibilities open interesting avenues for future research.

The results indicate that among those with more than 12 years of education, occupational and industry mobility increased for almost all of the age groups. Among those with 12 years of education or less, mobility increased significantly for workers younger than 40. Occupational and industry mobility did not change significantly for older, uneducated workers.

3.2.4. *Dynamics of overall mobility with a fixed population structure.* The increase in overall occupational and industry mobility is even more pronounced when we reweigh the sample to hold the demographic structure fixed. Using occupational mobility as an example, fixing the demographic structure in the probit regression to be the same as in 1980, it has increased from 11% to 16% at a one-digit level, from 13% to 18% at a two-digit level, and from 17% to 23% at a three-digit level. This finding is not particular to our choice of fixing the population structure to be the same as in 1980. We obtained essentially the same results when fixing the demographic structure to be the same as the average over the period, or as in 1970, or 1980, or 1990. The estimated time trend is positive, significant at 1%, and similar across all fixed population structures.

This finding suggests that the apparent slowdown in the rate of increase in mobility in the mid-1980s in Figures 2 and 3 that are based on the actual population

the number of digits in the occupational or industry classification. The extent of such nonmonotonicity turns out to be very minor.

[13] We find the hazard rate of an individual switching occupations declining sharply with the occupational tenure of that individual.

[14] Interestingly, there is evidence of a U-shape pattern of mobility with age, especially for educated workers. This pattern is more pronounced for occupations than industries. This is consistent with a model of on-the-job training that allows for human capital depreciation, as in Ben-Porath (1967). If workers find it optimal to let their specific human capital stock decline late in their working life, they become less attached to their sector of employment. Although high human capital workers may be reluctant to switch out of a sector that suffers a temporary decline in demand for its services, workers whose human capital has depreciated sufficiently may be more willing to switch.

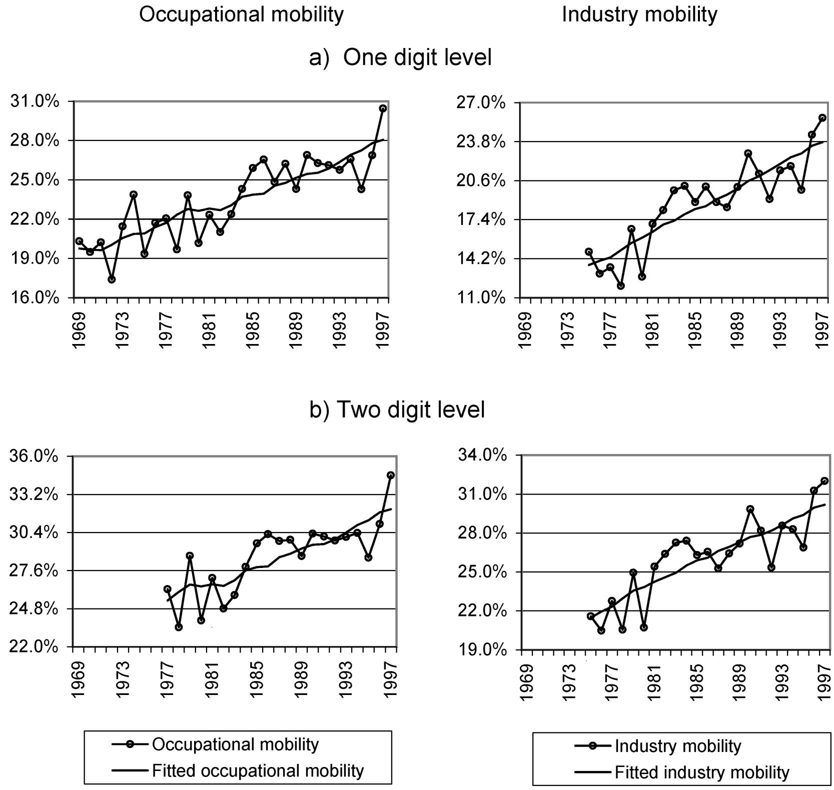


FIGURE 7

OCCUPATIONAL AND INDUSTRY MOBILITY IN THE UNITED STATES, 1969–97, ORIGINAL PSID CODING

structure may be entirely due to the composition bias. The share of high mobility age–education subgroups of the population is declining over time, and this effect partially offsets the increase in mobility within most groups.

## 4. SENSITIVITY ANALYSIS AND RELATED DISCUSSION

4.1. *Occupational and Industry Mobility as Revealed by the Originally Coded Data.* One check of the robustness of our finding of a significant increase in occupational and industry mobility in the United States over the 1968–97 period is to describe the level and the trend of occupational and industry mobility as revealed by the originally coded data.

Overall occupational and industry mobility, obtained from the originally coded data, is presented in Figure 7. The fitted occupational (industry) mobility for each year is obtained following the same empirical methodology as in Section 3 but excluding the variable *Break* and its interactions from the model, since there is no longer a break in the coding procedure in 1981. All of the panels in Figure 7 show a sharp increase in overall mobility. Occupational mobility increases from 20% in 1969 to 28% in 1997 at the one-digit level, and from 25% in 1977 to 32% in 1997 at the two-digit level. Industry mobility increases from 14% in 1975 to 24% in 1997 at the one-digit level, and from 22% in 1977 to 30% in 1997 at the two-digit level. The results in Parrado and Wolff (1999), who use originally coded data to study mobility at the one-digit level, imply a similar increase in mobility.[15]

Figure 8, which reports the fitted occupational and industry mobility by age–education groups, further validates our finding that the increase in occupational and industry mobility was pervasive. As we saw using the Retrospective Files, it also increased for most of the age–education subgroups of the population when we use only the originally coded data.[16]

Of course, since we are using the originally coded data in this subsection, the level of mobility is exaggerated by the presence of the measurement error in occupation and industry coding. For example, it implies that the average worker switches her aggregated two-digit occupation once every three years. The use of the Retrospective Files in the previous section revealed a much lower corrected level of mobility.

We will also use the Retrospective Files below to show that the trend in mobility identified in the originally coded data is informative. This is not clear ex ante because an increase in mobility on the originally coded data may have been driven by the increasing amount of the coding error over time. A simple reason may be that the PSID codes occupations and industries using the same 1970 classification that becomes more and more outdated over time. Or maybe the reallocation of workers from manufacturing to services resulted in a higher fraction of workers employed in sectors that are characterized by higher amount of coding error later in the period. We will show below that these hypotheses are not correct.

### 4.2. *Sensitivity to the Model Specification.*

4.2.1. *The effects of the coding error.* Our motivation for modeling the effect of the coding error as an affine shift came from Figure 1. Recall that from 1968 till 1980, at the one-digit level, we have information about one's occupation both in the Original and the Retrospective Files. First, using the Retrospective Files we computed one-digit occupational mobility and then fitted a linear probability version of model 1—the results are plotted as the two lower lines on Figure 1. Second, we computed one-digit occupational mobility on the originally coded

[15] We do not plot industry mobility in the years 1972–74, nor do we use it in the regression. We do so because industry mobility obtained from the originally coded data in those years is substantially higher than in any other year. The Retrospective Files do not exhibit such a pattern. It appears that there is something wrong with the original PSID coding of industry affiliation in those years. Loungani and Rogerson (1989) also report this problem.

[16] For an unclear to us reason, however, the originally coded data implies a relatively larger increase in mobility of older educated workers than what is implied by our analysis that used the Retrospective Files.

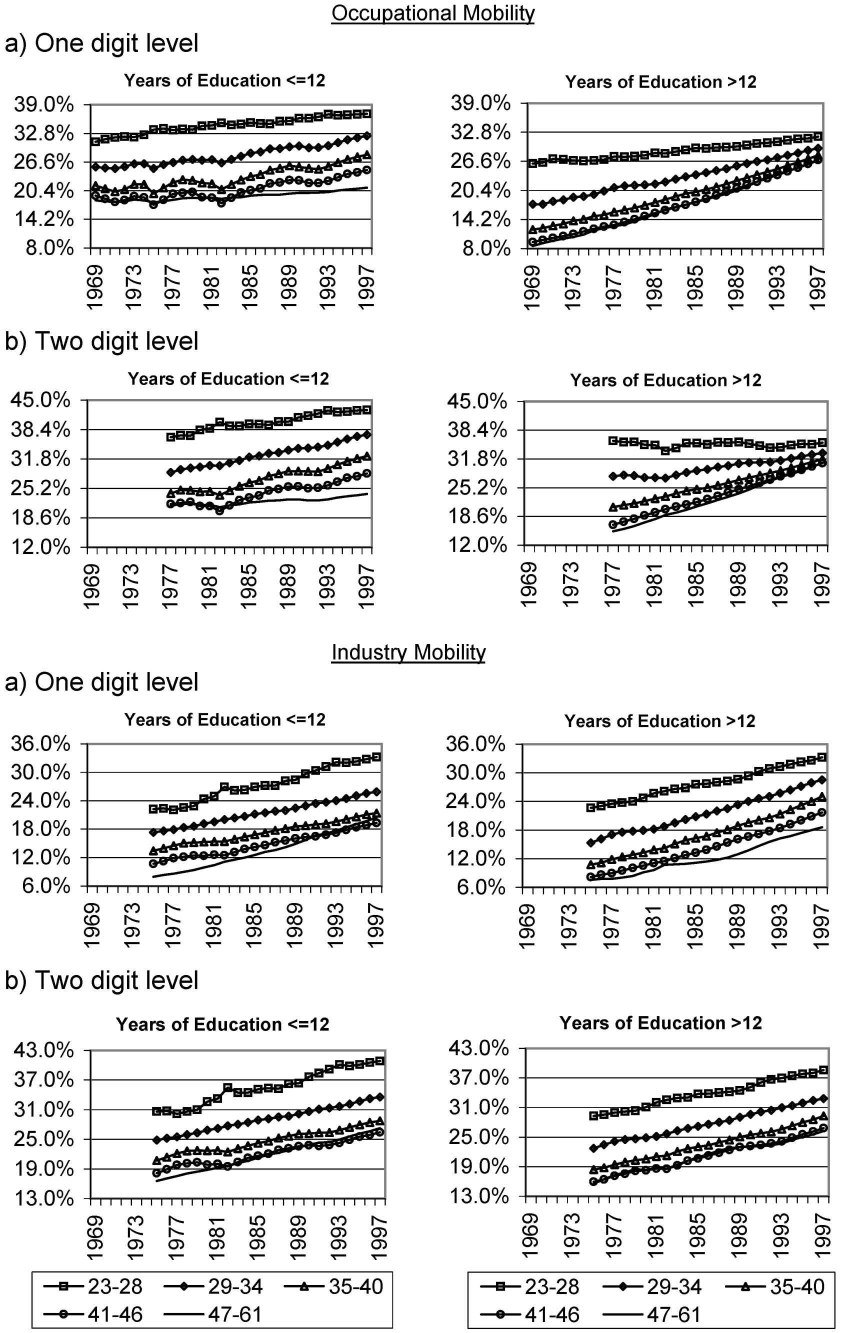


FIGURE 8

OCCUPATIONAL AND INDUSTRY MOBILITY IN THE UNITED STATES BY AGE AND EDUCATION LEVELS, 1969–97, ORIGINAL PSID CODING data and fitted a linear probability version of model 1 to it—the results are plotted as the two upper lines on Figure 1. Comparing the results from the Original and the Retrospective Files, we see that while mobility is higher on the originally coded data, the trend appears to be quite similar suggesting that the nature of the coding error is indeed such that it leads to an affine shift in mobility.

More formally, we test whether the derivative with respect to time in both regressions (one on the originally coded data, the other on the Retrospective Files) is the same. We cannot reject the hypothesis that it is the same at any conventional significance level ($p$-value of 0.7618) confirming that the coding error leads to only an affine shift in mobility.

Finally, we further test whether the coding error causes only an affine shift by estimating a linear probability model that includes, along with all the right hand side variables in Equation (1), the following variables:[17] $\beta_{24}$ *Time* $*$ *Break*, $\beta_{25}$ *Time* $*$ *Educ* $*$ *Break*, $\beta_{26}$ *Unemp* $*$ *Break*, $\beta_{27}$ *Unemp* $*$ *Educ* $*$ *Break*, $\beta_{28}$ *Time* $*$ *Age* $*$ *Break*, $\beta_{29}$ *Time* $*$ *Age* $*$ *Educ* $*$ *Break*, $\beta_{30}$ *Time* $*$ $Age^2$ $*$ *Break*, $\beta_{31}$ *Time* $*$ $Age^2$ $*$ *Educ* $*$ *Break*, $\beta_{32}$ *Unemp* $*$ *Age* $*$ *Break*, $\beta_{33}$ *Unemp* $*$ $Age^2$ $*$ *Break*, $\beta_{34}$ *Unemp* $*$ *Age* $*$ *Educ* $*$ *Break*, $\beta_{35}$ *Unemp* $*$ $Age^2$ $*$ *Educ* $*$ *Break*. Estimating the model that includes these terms, we find that they are highly statistically insignificant both individually and jointly. At the same time, the remaining interactions of the *Break* variable that are included in our baseline regression are mostly statistically significant individually and are highly significant jointly. This is again consistent with Figure 1, which suggests that the coding error causes an affine shift with a minor effect on the time trend.

The specification that we have adopted for the linear probability model is consistent with the coding error resulting in an affine shift only. A complication arises in the case when $\xi$ is not linear, for example, in the case of a probit regression. Given our way of adjusting the figures that are based on the probit regression, our analysis is conservative in the sense that it provides a lower bound on the increase in mobility. This is due to the convexity of the left tail of the cumulative standard normal distribution and the facts that the estimates of the trend we obtain are positive and that the probability of a switch does not exceed 50%. In other words, since $\beta X$ is increasing linearly with time, the effect of the affine shifter *Break* increases more than linearly with time. Thus, in the probit regression we obtain an increasing coding error despite the affine shift inside the probit function. Thus, the way of adjusting Figures 3–6, 9, and 10 that we adopt represents the lower bound on the mobility increase over the 1981–97 period.

Alternatively, we could obtain an estimate of the coding error in, say, 1981, or compute an average coding error in the 1981–97 period and subtract this one value from each observation after 1980. Under such a procedure, the overall mobility increases would, on average, be one percentage point larger than the ones in Figures 3–6, 9, and 10. We do not include these figures into the paper since under such

[17] This specification is consistent with the linear version of the following simple model of the coding error. Suppose that there is a probability $p$ that a worker is erroneously misclassified as having switched sectors in date $t$ in the originally coded data. This implies Pr ($i$ recorded as having switched) $= [1 - \xi(\beta\ X)]p + \xi(\beta\ X)$.

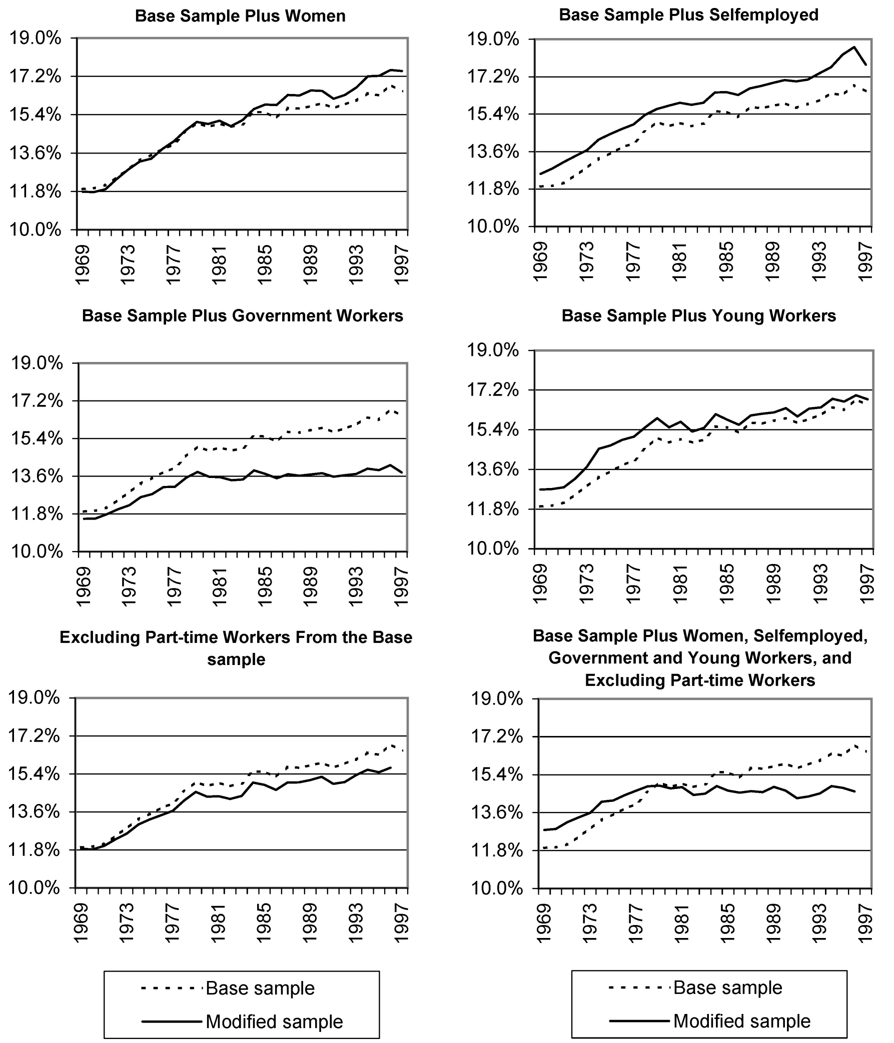


FIGURE 9

OCCUPATIONAL MOBILITY IN THE UNITED STATES, 1969–97, TWO-DIGIT LEVEL: DIFFERENT SAMPLE RESTRICTIONS

a procedure the estimated increase in mobility from the probit model is virtually the same as the one obtained from the linear probability model presented in Figure 2 (which also suggest approximately one percentage point larger increases in mobility).[18]

[18] A difficult but potentially useful alternative approach is to write down a model of the coding error, and estimate its effects by maximum likelihood.

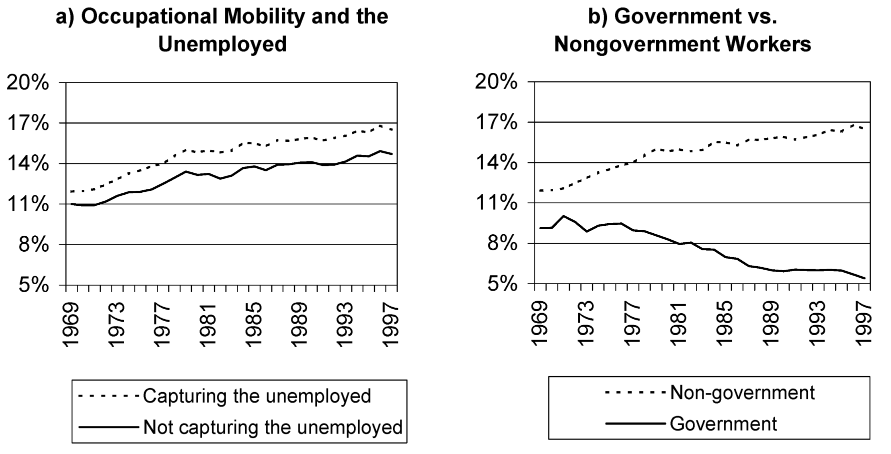


FIGURE 10

OCCUPATIONAL MOBILITY IN THE UNITED STATES, 1969–97, TWO DIGIT LEVEL

*Notes:* THE DOTTED LINE ON PANELS (A) AND (B) SHOWS OCCUPATIONAL MOBILITY ON OUR BASE SAMPLE WHICH INCLUDES MALE HEADS OF HOUSEHOLD, AGED 23–61, WHO ARE NOT SELF-EMPLOYED, OR DUAL-EMPLOYED, AND ARE NOT WORKING FOR THE GOVERNMENT. THE SOLID LINE ON PANEL (A) SHOWS OCCUPATIONAL MOBILITY WHEN THE BASE SAMPLE IS RESTRICTED TO THOSE EMPLOYED IN BOTH YEARS. THE SOLID LINE IN PANEL (B) SHOWS OCCUPATIONAL MOBILITY WHEN WE CONSIDER THE SAMPLE OF GOVERNMENT WORKERS ONLY.

4.2.2. *Parametric assumptions.* The fact that the model is estimated on our full sample, as opposed to being estimated separately for each age–education subgroup, does not drive our results. In Kambourov and Manovskii (2004d)—a working paper version of this article—we characterized worker mobility without imposing any structure on the relationship of mobility across age–education groups and obtained very similar results. We have also experimented with imposing a cubic polynomial structure in age and a quadratic in time with no noticeable change in the results.

4.3. *Sensitivity of the Empirical Results to the Sample Restrictions.* In this subsection we provide evidence that our results are robust to numerous variations in the sample selection criteria. Our usual sample, called the base sample here, is restricted to male heads of household, aged 23–61, who are not self- or dual-employed and are not working for the government. In Figure 9, we show how the measure of occupational mobility at the two-digit level (the choice to present the results at the two-digit level is inconsequential for the message of this subsection) is affected if we relax some of the imposed sample restrictions. The addition of women to the base sample makes the increase in mobility slightly bigger, and the addition of self-employed workers shifts up the mobility graph without affecting its slope. Adding government workers to the base sample makes the increase in mobility two percentage points lower than what it would otherwise have been (more on this below). Adding workers who are 18—22 years old raises the level of occupational mobility in all years, although the overall increase in mobility over the period is one percentage point lower than in the base sample. Restricting the base sample to full-time workers only (those who report working at least 1,500 hours in a given year) results in an increase in mobility that is 0.5 percentage points lower than in the base sample. Finally, simultaneously incorporating all of the above restrictions leads to a smaller increase in occupational mobility.

4.4. *Occupational Mobility and Unemployed Workers.* One advantage of using the PSID data to study occupational and industry mobility is that the PSID, being a panel data set, allows us to follow individuals through unemployment spells. If a worker is employed at the interview date in year $t$, unemployed in year $t+1$, and employed again in year $t+2$ in a different occupation, the PSID allows us to capture this occupational switch. If one uses the (March) CPS, for instance, this occupational switch will not be captured, since in year $t+2$, the CPS provides information only on the worker's current occupation and last year's occupation but not on the occupation in period $t$. To compute occupational (industry) mobility in the CPS, one needs to restrict the sample to workers who are employed in two consecutive years and consider what fraction of this sample changed occupations (industries).

Figure 10a compares our preferred measure of occupational mobility at the two-digit level with the one obtained on the sample of workers employed in two consecutive years. Two conclusions emerge. First, not taking the unemployed individuals into account reduces the measured level of occupational mobility by around 2.5 percentage points. Second, the trend in occupational mobility is slightly different: The second measure exhibits a smaller increase in mobility in the 1980s. This evidence suggests that workers in the 1980s might have been facing more fundamental occupational changes requiring a higher degree of skill upgrading and retooling and longer periods of transition from one occupation to another. This is consistent with the evidence in Murphy and Topel (1987), who report that the rise in unemployment in the 1970s and early 1980s was almost entirely due to the rise in the incidence of long spells of unemployment.

Note that since the PSID sample starts in 1968, in 1969 we compute mobility on the sample of those who were employed in 1968 and 1969. According to the discussion above, this may bias downward our mobility measure in 1969. Fortunately, 1968 was a very low unemployment year—only 4.2% of the workers in our sample were unemployed in 1968. Furthermore, by 1969 91% of them were already re-employed. That implies that the mobility from 1970 on is accurately computed.

4.5. *Occupational Mobility of Government Workers.* The pattern of occupational mobility exhibited by government workers is markedly different from the observed general pattern. We define occupational mobility for government workers in year $t$ as the fraction of government workers who in year $t$ work in an occupation that is different from the one they worked in in year $t-1$ or the last time they were employed. Most of the occupational switches thus identified represent workers changing occupations within the government instead of workers entering the government sector and starting in a new occupation.

Figure 10b shows two-digit occupational mobility for government workers for the period 1969–97. Two observations are noteworthy. First, occupational mobility for government workers is two times lower—around 8%—than the mobility of workers in the private sector. Second, occupational mobility of government workers has declined sharply over the period—from 10% in the late 1960s to 6% in the early 1990s. These facts explain why including government workers in the sample decreases the overall level and flattens the upward trend in occupational mobility.

The trend in occupational and industry mobility of government workers is in such contrast to that of private-sector workers that it begs for a rigorous investigation of its sources. One possible explanation for this observation may be the change in the occupational mix employed by the government, due to, for example, contracting out of many government-provided services.

4.6. *Occupational Mobility and the Reallocation of the Labor Force from Manufacturing into Services.* During the 1968–97 period there was a substantial change in the employment shares of various broad sectors of the economy. For instance, whereas the share of manufacturing declined, the share of the service sector increased. In this subsection we evaluate two hypotheses. First, we ask whether the increase in mobility could be explained by workers moving into sectors that are characterized by higher amount of coding error. Second, we ask if the increase in mobility was caused by a changing sectoral composition of the economy in favor of sectors with genuinely higher worker mobility. The answer to both questions is no.

We divide our sample into growing and declining one-digit sectors. Agriculture, mining, construction, and manufacturing are all sectors whose employment share declined over the period. The sectors that experienced an increase in their employment share are transportation and communications, wholesale and retail trade, personal services, and finance and insurance. During the 1977–80 period we have both the true two-digit occupational switches from the Retrospective Files and the noisy switches from the originally coded data.

To address the first question we compute the fraction of workers in each sector who did not switch their occupations in the reliable retrospective data, but would be wrongly classified as switchers in the originally coded data. We find that the coding error is higher in the declining sectors. For instance, 19% of the nonswitchers are wrongly classified as switchers in manufacturing, 21% in mining, and 21% in construction. That fraction is only 12% in wholesale and retail trade, 15% in the finance and insurance sector, and 13% in the personal services sector. This implies that the sectoral composition of the economy has changed in favor of sectors with a lower amount of coding error. Thus, the documented increase in mobility represents a lower bound on the true increase.

To answer the second question, we compute occupational mobility within each broad sector using the reliable data from the Retrospective Files for the 1969–80 period. We find that true occupational mobility within the growing sectors was lower than within the declining ones. For example, occupational mobility at the two-digit level is around 10% in manufacturing, 9% in construction, and

10% in mining. Within the service sectors, however, it is lower: around 7% in transportation and communications, 9% in wholesale and retail trade, 7% in the finance and insurance sector, and 5% in the personal services sector. This implies that changes in the sectoral composition tended to offset the increase in mobility that we found.

4.7. *Is Fixing the Occupational and Industry Classification over the Period Appropriate?* As mentioned above, the PSID uses the same 1970 Census of Population occupation and industry codes throughout the 1968–97 period. Clearly, some of the occupations people worked in in the early 1990s were not even in existence when the 1970 Census classification was developed. How does this affect the levels and trends in mobility that we document in this paper? When new occupations appear, workers in those occupations will be coded as belonging to the "not elsewhere classified" occupational categories of the outdated classification. This implies that, over time, these "not elsewhere classified" occupations themselves represent collections of new occupations. Because we cannot identify switches across those occupations, over time we necessarily identify a smaller and smaller fraction of occupational switches.[19] This implies that the increase in occupational and industry mobility documented in this paper represents a lower bound on the true increase. This downward bias is likely especially strong on the three-digit level.

It does not appear feasible to identify by how much we underestimate mobility late in the sample owing to the use of the 1970 classification. One may consider using the March CPS, which changed its occupational and industry classifications three times during the 1968–97 period. Unfortunately, each successive occupational classification not only introduces new occupations but also aggregates some of the existing ones. As a consequence, in the March CPS data, occupational mobility *declines* each time a new classification is introduced. This makes the interpretation of trends in occupational mobility obtained from the March CPS difficult.

## 5. ADDITIONAL FACTS ON WORKER MOBILITY

5.1. *Net Occupational Mobility.* So far we have studied the gross reallocation of workers across occupations and industries. In this section we study the behavior of the net reallocation, defined as one-half of the sum of the absolute changes in occupational employment shares, i.e., if $s_{m,t}$ is the fraction of employment in occupation $m$ in year $t$, net mobility in year $t$ is given by $1/2 \sum_m |s_{m,t} - s_{m,t-1}|$.

The analysis in this section provides insights into the reasons for the observed high levels of gross mobility. In particular, if mobility is primarily caused by shifting demands for labor in different sectors of the economy (as in Lucas and Prescott, 1974), gross flows of workers should approximately equal net flows. If, however, it turns out that gross flows dwarf net flows, this would point the quest for

[19] The fraction of workers in our sample employed in the "not elsewhere classified" occupational categories increases from 14% to 21% over the 1968–97 period.

understanding workers' mobility decisions toward studying the matching process between workers and occupations (as in Jovanovic, 1979; Miller, 1984; McCall, 1990).[20]

As pointed out earlier in the paper, until 1980 the Retrospective Files provide us with reliable information on sectoral affiliations in the economy, whereas after 1980 we are restricted to using the noisy originally coded data. When studying gross occupational mobility, it is imperative to control for the coding error after 1980. In the case of net mobility, however, the issue is more subtle. If one individual could be wrongly misclassified from occupation $x$ into occupation $y$, then it is conceivable that another worker might be misclassified from occupation $y$ into occupation $x$. Such switches cancel out, leaving no effect on computed net mobility. To estimate the contribution of the coding error to net mobility, we regressed net occupational mobility on a constant, time trend, unemployment, and a dummy variable *Break*, which takes the value of one for all years after 1980. Then, in reporting net occupational mobility in Figure 11, we subtract the estimated coding error as given by the coefficient on the *Break* variable. Consistent with the discussion above, at the one- and two-digit levels, the estimated coding error is very small and statistically insignificant, and controlling for it turns out to be almost inconsequential for the reported results. We find that at the one-digit level, net mobility increases from 1% to over 3% over the 1970–97 period, whereas at the two-digit level the increase is from 3% to 6%. At the three-digit level, the estimate of the coding error is larger and statistically significant. In particular, net occupational mobility increases from 9% to 15% if one does not account for the coding error post 1980, and from 9% to 13%, if one does.

We conclude that net occupational mobility is high and that the increase in gross mobility over the 1968–97 period is accompanied by an increase in net mobility.[21] This lends support to the hypothesis that the rise in gross occupational mobility is attributable to the increased variability of occupational labor demands.

5.2. *The Extent of Return Mobility.* An important question that restricts the theories of worker mobility is how permanent occupational and industry switches are. To address this issue, we compute the fraction of workers who switch their occupations (industries) and then return to the original occupations (industries) one, two, and three years after the switch. The Retrospective Files are appropriate for computing this statistic. For each of the years from 1969 till 1977, we identify those workers who have just switched their occupation (industry), and then we follow them for three years in order to determine the fraction that returns to their original occupation (industry). The reported statistics are averaged over the period.

[20] Jovanovic and Moffitt (1990) study the relative importance of sectoral shocks and employer–worker mismatch in explaining sectoral reallocation. They, however, use only three very aggregated sectors: manufacturing, services and trade, and other industries.

[21] As opposed to the level of gross mobility, the levels of net mobility found in the PSID should be interpreted with caution because of the relatively small PSID sample size.

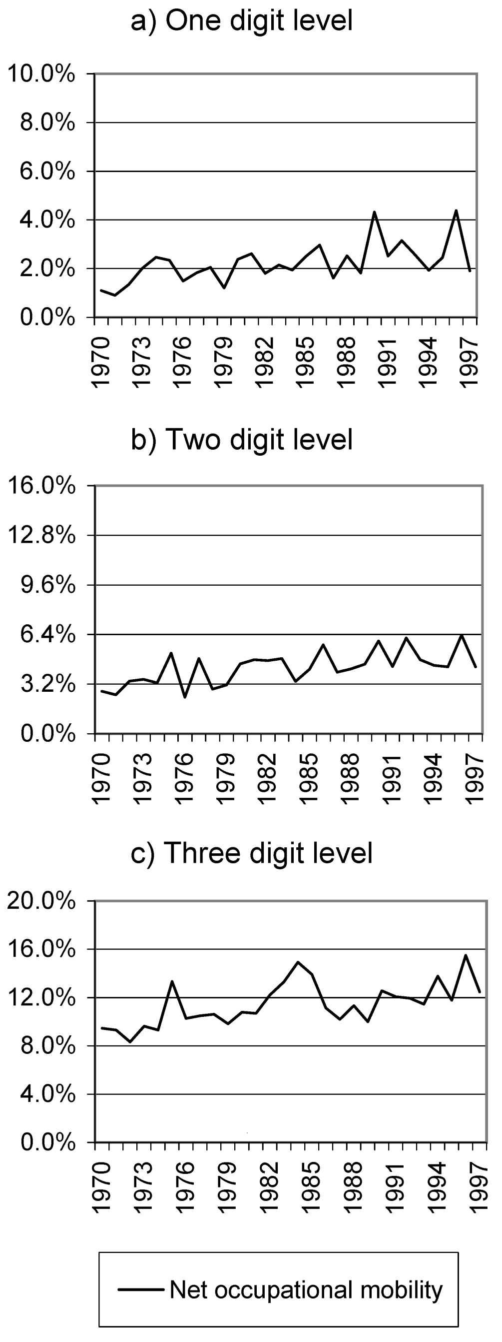


FIGURE 11

NET OCCUPATIONAL MOBILITY IN THE UNITED STATES, 1970–97

TABLE 4
FRACTION OF WORKERS RETURNING TO THEIR OCCUPATION OR INDUSTRY, 1969–80

| | Fraction of Workers Returning After | | |
|---|---|---|---|
| Variable | One Year | Two Years | Three Years |
| 1-Digit Occupation | 0.1948 | 0.1063 | 0.0630 |
| | (0.0100) | (0.0078) | (0.0062) |
| 2-Digit Occupation | 0.1673 | 0.0862 | 0.0521 |
| | (0.0095) | (0.0071) | (0.0057) |
| 3-Digit Occupation | 0.1180 | 0.0562 | 0.0354 |
| | (0.0082) | (0.0058) | (0.0046) |
| 1-Digit Industry | 0.1846 | 0.0614 | 0.0606 |
| | (0.0098) | (0.0058) | (0.0061) |
| 2-Digit Industry | 0.1453 | 0.0465 | 0.0507 |
| | (0.0089) | (0.0052) | (0.0055) |
| 3-Digit Industry | 0.1194 | 0.0350 | 0.0477 |
| | (0.0081) | (0.0047) | (0.0053) |

NOTES: Each cell represents the fractions of workers who return to their occupation (industry) one year, two years, or three years after they have switched them. Standard errors are in parentheses. The results are obtained using the Retrospective Files for the period 1969–80. For each of the years from 1970 till 1977 we identify those workers who have just switched their occupation (industry), and then we follow them for three years in order to determine the fraction that returns to their previous occupation (industry). The reported statistics are averaged over this period.

The results summarized in Table 4 indicate that around 30% of workers return to their one-digit occupation (industry) within a three-year period, and around 20% return to their three-digit occupation (industry). These estimates are in line with those reported by Loungani and Rogerson (1989) for two-digit industry switches. The probability of return declines sharply with years after the switch.

5.3. *Occupational Mobility across Broad Occupational Groups.* Why is mobility of college-educated workers so high and increasing? A conjecture often offered is that this might be due to upward career mobility into management positions. Therefore, we take a more detailed look at the nature of the observed occupational switches. We show that although some of the increase in mobility in the high-skilled occupations indeed came from moves into management positions, an equal fraction involved moves into occupations typically employing lower-skilled workers.

We study the patterns of occupational switches over time across six large occupational groups that correspond to the one-digit occupational classification: group 1—professional, technical, and kindred workers; group 2—managers, officials, and proprietors; group 3—clerical and sales workers; group 4—craftsmen, foremen, and kindred workers; group 5—operatives and kindred workers; and group 6—laborers and service workers. Unfortunately, we cannot use a finer occupational partition because the sample size would be too small to precisely estimate all the implied occupational transitions. For comparability across time, we use originally coded data for this analysis. Thus, although the implied level of mobility is too high, the trends are informative.

We concentrate the analysis on three time periods: 1969–75, 1979–85, and 1989–95. The procedure is as follows. We count those employed in a given year in occupation $i$ who will be working the following year in occupation $j$ and divide this by the number of those who are employed today in occupation $i$ and who will report any occupation next year (by doing so we effectively restrict the sample to those employed and reporting occupations in both years). This is done in each year in the specified time period, and the average result weighted by the PSID sample weights is reported in the cell $ij$ of Table 5.[22]

The results confirm our findings of increased overall occupational mobility. Except for group 5, where the fraction of stayers remains quite similar over time, all other occupational groups exhibit a significant decrease in the fraction of workers who remain in those occupations from one year to the next. Consistent with our earlier findings, the increase in mobility is not limited to occupations that employ mainly highly educated (groups 1 and 2) or mainly uneducated workers (groups 3, 4, and 6).

The mobility of those who move out of educated groups like 1 and 2 is particularly interesting. The data indicate that although some of the increase in mobility from educated groups comes from occupation switches between groups 1 and 2, a higher fraction of workers in those occupational categories are moving into less educated occupational groups. In fact, whereas in the 1969–75 period, on average 4.34% of workers in group 1 switched to groups 3 to 6 from one year to the next, in the 1989–95 period 8.67% did. The corresponding numbers for group 2 workers are 11.25% and 16.58%.

Note that the results of this subsection are not driven by business cycle effects. All three periods represent roughly the same business cycle characteristics. We have performed similar analysis for selected years only, and the results are essentially the same. The analysis suggests that the increase in occupational mobility was not limited to a subset of particular one-digit occupations. In this sense the increase in occupational mobility was pervasive.

The analysis in this subsection also sheds light on the hypothesis in Jovanovic and Nyarko (1997) that many occupations serve as stepping-stones or springboards for other occupations and this accounts for a substantial fraction of occupational mobility. As noted in McCall (1990), under this hypothesis our Table 5 should be very asymmetric across the diagonal. The fact that this is not the case implies that we cannot order one-digit occupations to form a sequence in a typical career path. Perhaps one must look at more disaggregated occupations for evidence of stepping-stone mobility.

5.4. *Mobility across Occupation–Industry Cells.* In this subsection we briefly characterize the mobility across occupation–industry cells. It is defined as the

[22] The results obtained on the unweighted sample are similar.

TABLE 5

MOBILITY ACROSS BROAD OCCUPATIONAL GROUPS

A. Average Mobility over the 1969–1975 Period

| From | To 1 | 2 | 3 | 4 | 5 | 6 | Relative Size |
|---|---|---|---|---|---|---|---|
| 1 | 0.9144 | 0.0423 | 0.0203 | 0.0138 | 0.0052 | 0.0041 | 0.1747 |
| | (.0076) | (.0055) | (.0038) | (.0032) | (.0020) | (.0017) | (.0038) |
| 2 | 0.0408 | 0.8467 | 0.0560 | 0.0341 | 0.0179 | 0.0045 | 0.1332 |
| | (.0063) | (.0115) | (.0073) | (.0058) | (.0042) | (.0021) | (.0034) |
| 3 | 0.0388 | 0.0966 | 0.7973 | 0.0303 | 0.0405 | 0.0149 | 0.1086 |
| | (.0061) | (.0094) | (.0128) | (.0054) | (.0063) | (.0038) | (.0031) |
| 4 | 0.0090 | 0.0197 | 0.0197 | 0.8170 | 0.1083 | 0.0263 | 0.2793 |
| | (.0019) | (.0027) | (.0027) | (.0076) | (.0061) | (.0032) | (.0044) |
| 5 | 0.0085 | 0.0089 | 0.0219 | 0.1470 | 0.7373 | 0.0764 | 0.2154 |
| | (.0018) | (.0018) | (.0028) | (.0068) | (.0084) | (.0051) | (.0041) |
| 6 | 0.0057 | 0.0201 | 0.0138 | 0.0920 | 0.1730 | 0.6953 | 0.0869 |
| | (.0019) | (.0035) | (.0029) | (.0073) | (.0095) | (.0116) | (.0028) |

B. Average Mobility over the 1979–1985 Period

| From | To 1 | 2 | 3 | 4 | 5 | 6 | Relative Size |
|---|---|---|---|---|---|---|---|
| 1 | 0.8413 | 0.0750 | 0.0329 | 0.0361 | 0.0079 | 0.0067 | 0.1692 |
| | (.0091) | (.0066) | (.0044) | (.0047) | (.0022) | (.0020) | (.0034) |
| 2 | 0.0703 | 0.8096 | 0.0668 | 0.0338 | 0.0096 | 0.0098 | 0.1741 |
| | (.0066) | (.0101) | (.0064) | (.0046) | (.0025) | (.0025) | (.0035) |
| 3 | 0.0537 | 0.1005 | 0.7243 | 0.0445 | 0.0378 | 0.0391 | 0.1112 |
| | (.0066) | (.0088) | (.0130) | (.0060) | (.0056) | (.0056) | (.0029) |
| 4 | 0.0276 | 0.0363 | 0.0178 | 0.7947 | 0.0888 | 0.0348 | 0.2657 |
| | (.0030) | (.0034) | (.0024) | (.0073) | (.0052) | (.0033) | (.0041) |
| 5 | 0.0096 | 0.0117 | 0.0170 | 0.1261 | 0.7771 | 0.0586 | 0.1961 |
| | (.0018) | (.0019) | (.0023) | (.0060) | (.0075) | (.0043) | (.0036) |
| 6 | 0.0110 | 0.0433 | 0.0475 | 0.0902 | 0.1693 | 0.6387 | 0.0837 |
| | (.0028) | (.0054) | (.0057) | (.0076) | (.0099) | (.0127) | (.0025) |

C. Average Mobility over the 1989–1995 Period

| From | To 1 | 2 | 3 | 4 | 5 | 6 | Relative Size |
|---|---|---|---|---|---|---|---|
| 1 | 0.8221 | 0.0912 | 0.0288 | 0.0333 | 0.0146 | 0.0100 | 0.1985 |
| | (.0082) | (.0061) | (.0036) | (.0038) | (.0026) | (.0021) | (.0034) |
| 2 | 0.0916 | 0.7427 | 0.0735 | 0.0579 | 0.0170 | 0.0174 | 0.1939 |
| | (.0063) | (.0096) | (.0057) | (.0051) | (.0028) | (.0029) | (.0034) |
| 3 | 0.0642 | 0.1280 | 0.6946 | 0.0316 | 0.0357 | 0.0459 | 0.1179 |
| | (.0064) | (.0087) | (.0119) | (.0045) | (.0048) | (.0054) | (.0028) |
| 4 | 0.0427 | 0.0493 | 0.0209 | 0.7592 | 0.0809 | 0.0470 | 0.2138 |
| | (.0036) | (.0038) | (.0026) | (.0076) | (.0048) | (.0038) | (.0035) |
| 5 | 0.0198 | 0.0198 | 0.0226 | 0.1009 | 0.7688 | 0.0681 | 0.1846 |
| | (.0025) | (.0025) | (.0027) | (.0054) | (.0076) | (.0045) | (.0033) |
| 6 | 0.0221 | 0.0411 | 0.0474 | 0.1028 | 0.1489 | 0.6377 | 0.0912 |
| | (.0036) | (.0048) | (.0051) | (.0074) | (.0086) | (.0116) | (.0025) |

NOTE: Cell *ij* represents the average (over the period) percent of those working in occupation *i* in a given year who will work in occupation *j* the following year. Occupational groups are defined as: 1. Professional, technical, and kindred workers; 2. Managers, officials, and proprietors; 3. Clerical and sales workers; 4. Craftsmen, foremen, and kindred workers; 5. Operatives and kindred workers; 6. Laborers and service workers. Standard errors are in parentheses.

fraction of currently employed individuals who report a current occupation–industry pair both elements of which are different from their most recent previous report of an occupation–industry pair. Mobility across occupation–industry cells was used as a measure of career mobility in Neal (1999). Since there may be instances where skills are transferable both across industries within an occupation and across occupations within an industry, Neal decided to identify only changes in both occupation and industry as transitions that involve a loss in human capital. In addition, such definition of mobility may be useful for researchers who work with data sets other than the PSID and face the problem of measurement error in the occupation and industry coding. In Kambourov and Manovskii (2004d)—a working paper version of this article—we show that switching both an occupation and an industry is more likely to identify true switches instead of erroneous miscoding.

As Figures 12 and 13 illustrate, mobility across occupation–industry cells is naturally lower than either occupational or industry mobility. It has increased significantly over time.

5.5. *Occupational Mobility over the Business Cycle.* A detailed analysis of the behavior of occupational (industry) mobility over the business cycle is called for but is beyond the scope of this paper. Here we make some basic observations. We find that net occupational (industry) mobility is countercyclical, whereas gross mobility is mildly procyclical. As is evident from Figure 14, however, this masks the different patterns of behavior of various age–education subgroups over the business cycle. Figure 14 shows the effect of a marginal increase in the unemployment rate on occupational mobility at the three-digit level. Two observations stand out. First, for both education groups, occupational mobility is countercyclical for the young and old workers and procyclical for the middle-aged workers. Second, whereas occupational mobility of workers with education levels of high school or less is strongly affected by the business cycle conditions, the mobility of college-educated workers is much less influenced by the business cycle. These findings suggest a potentially important type of worker heterogeneity so far overlooked in the analysis of the welfare costs of business cycles.

## 6. CONCLUSION

The analysis in this paper was designed to provide a set of key facts characterizing the patterns of occupational and industry mobility in the U.S. over the 1968–97 period. We document that occupational and industry mobility is high and has increased substantially over the period. In addition, we show that this constitutes a profound change in the labor market that has affected a large fraction of the labor force. For instance, occupational mobility has increased for most age–education groups, and its rise was not driven by an increased flow of workers into or out of a particular one-digit occupation.

A key contribution of the analysis was the use of the Retrospective Files, which are the best data available on annual occupational and industry mobility in the United States. These data generated estimates of mobility that are considerably

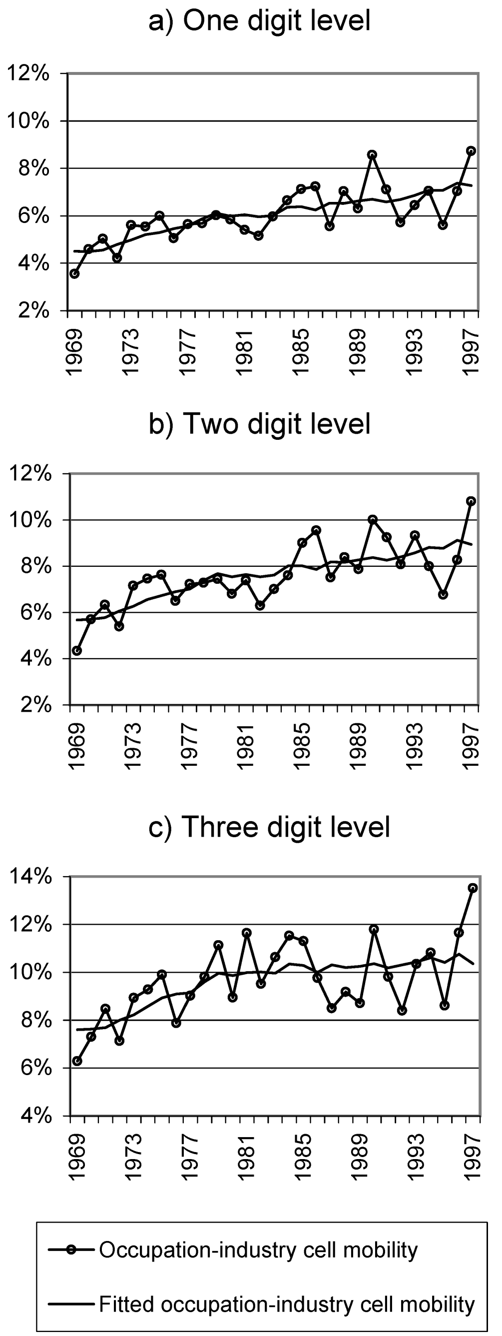


FIGURE 12

MOBILITY ACROSS OCCUPATION–INDUSTRY CELLS IN THE UNITED STATES, 1969–97, PROBIT REGRESSION

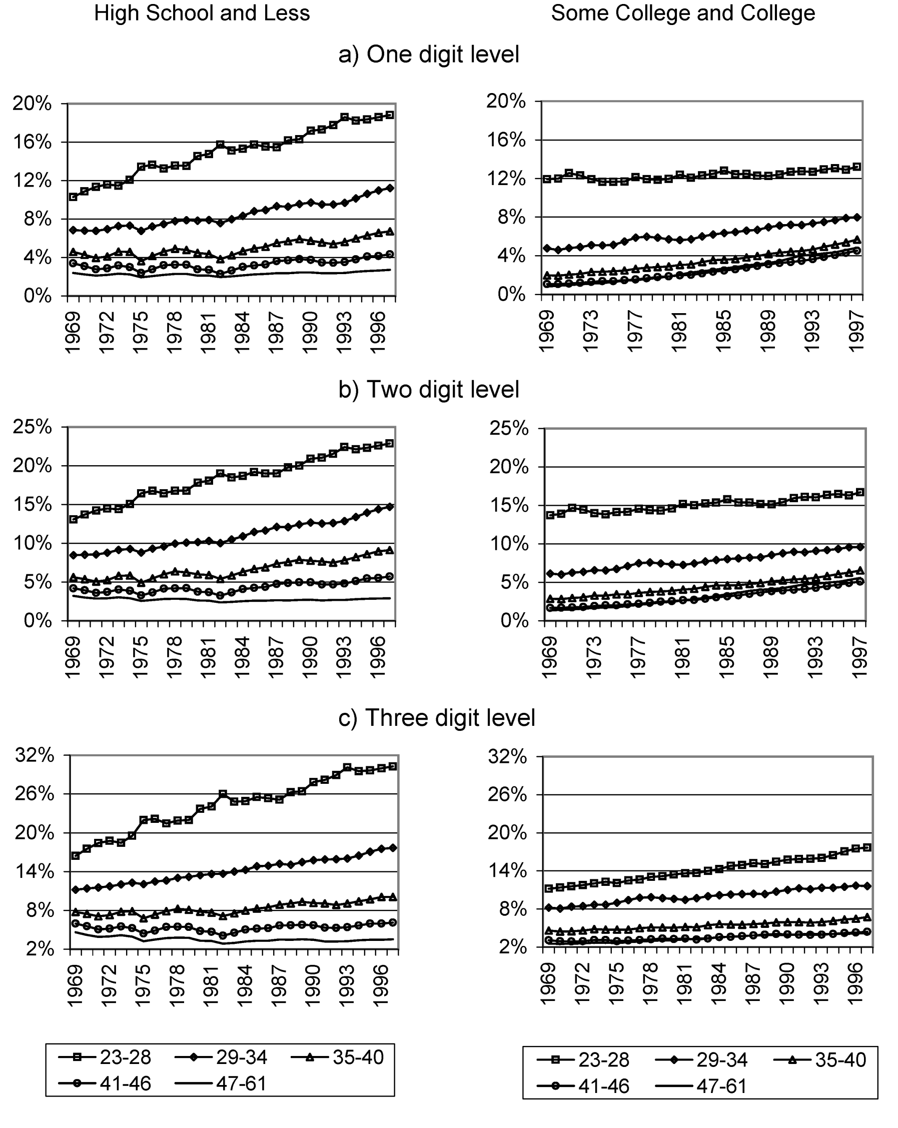


FIGURE 13

MOBILITY ACROSS OCCUPATION–INDUSTRY CELLS IN THE UNITED STATES BY AGE AND EDUCATION LEVELS, 1969–97

lower than those found in the rest of the literature. In addition, it gave us confidence in interpreting the trends in mobility. It turned out that the trends in mobility are very similar in the originally coded data and in the Retrospective Files. Because these data were coded at different time and using different methodologies, one cannot argue that the trend in mobility was attributable to a trend in the coding error.

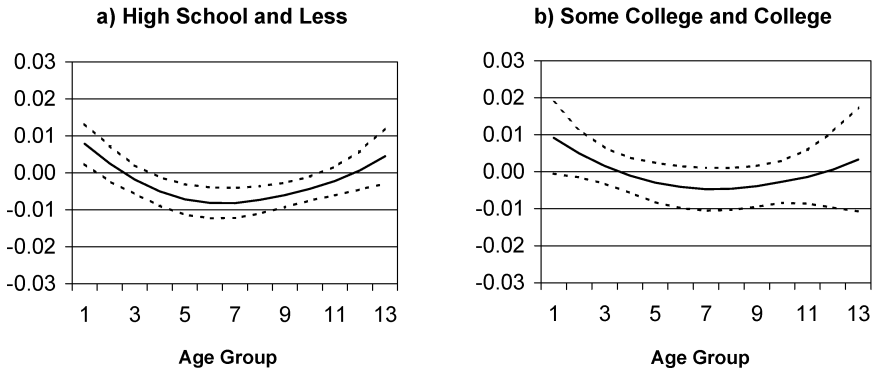


FIGURE 14

OCCUPATIONAL MOBILITY OVER THE BUSINESS CYCLE, BY AGE AND EDUCATION, THREE-DIGIT LEVEL
*Notes:* THE SOLID LINES SHOW THE EFFECT OF A MARGINAL INCREASE IN THE UNEMPLOYMENT RATE ON OCCUPATIONAL MOBILITY FOR EACH OF THE 13 THREE-YEAR AGE GROUPS STARTING FROM THE AGE OF 23. THE DOTTED LINES SHOW THE RESPECTIVE 95% CONFIDENCE INTERVALS.

We defined occupations and industries using the one-, two-, and three-digit classifications used by the 1970 Census of Population and provided by the Panel Study of Income Dynamics for the 1968–97 period. The examination of the occupational titles suggests that human capital is likely to be three-digit instead of one- or two-digit specific. A close look at the three-digit occupation classification reveals that skills accumulated in a given three-digit occupation may not be easily transferable to another three-digit occupation. For example, if an economics professor becomes a psychologist or a librarian, then, despite staying in the same one- and two-digit occupation, she would not be able to use most of the human capital she accumulated while in economics. Results in Kambourov and Manovskii (2002) confirm this intuition. Specifically, they find that the returns to five years of occupational experience are as high as at least 8% at the one-digit level, 10% at the two-digit level, and 12% at the three-digit level. Thus, we suggest that researchers interested in calibrating models of worker mobility associated with human capital changes should use the levels and trends in occupational mobility at the three-digit level.

Even the three-digit occupational classification, however, may not perfectly represent the specific human capital. First, a finer partition may be required for some three-digit occupations such as, for example, computer programmers (003) or medical and osteopathic physicians (065). Second, there may exist subsets of the three-digit occupational classification such that no human capital is destroyed when switching occupations within such a subset. Possible examples are a salesman (260) who becomes sales manager (231/233), or an assembler (602) who becomes a foreman (441), or bookkeeper (305, 341) who becomes an accountant (001), or a health service worker (921–926) who becomes a health technician (080–085). Although the data availability do not permit one to address the first concern, it appears interesting but difficult to construct a metric of how transferable occupational experience is between two given occupations. It remains true, however, that everything else being constant, the average worker with five years of occupational tenure would see his wages decline by at least 12% upon an occupation switch because many of the skills accumulated in the previous occupation are not used any longer and new skills need to be developed.

In view of this sharp rise in mobility, the next logical step is the investigation of the causes of its increase. Kambourov and Manovskii (2004b) suggest that the variability of occupational demand shocks has increased over time. They also argue in a general equilibrium model that the increase in mobility was not likely to be caused by a decline in the costs of switching occupations. Other potential causes of the increased mobility include technological change, globalization and international trade, changes in government regulation, and labor force unionization. An intriguing research question is to relate changes in occupational mobility to changes in the growth rate of productivity. It may not be a coincidence that the increase in occupational mobility has coincided with the much discussed slowdown in productivity growth.

We think that this paper raises an important set of research questions. Why do people switch their occupations so often? Why has occupational mobility increased so much in the last 30 years? Is the increase in occupational mobility important for understanding the changes in wage inequality and the aggregate performance of the economy? We believe that answering these and other related questions will significantly advance our understanding of labor markets.

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