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Occupational and industrial mobility in the United States

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Abstract

Using the Panel Study of Income Dynamics, and using both the original and the new series of occupation and industry codes, we investigate occupational and industrial mobility of individuals over the 1969–1980 and 1981–1993 periods in the U.S. We find that workers changed both occupations and industries more frequently in the later period. We also find that for men occupational and industrial changes are associated with lower earnings, though this effect has lessened somewhat over time; while for women the results are mixed. Our results also indicate that older and better paid men are less likely to shift occupation or industry.
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1. Introduction

The U.S. economy has witnessed substantial structural change over the last three decades. First, employment has shifted from goods-producing industries to services. Second, since the 1970s, a rapid increase in the introduction of new information-based technologies has occurred. Third, this has been accompanied by substantial adjustments in operations and organizational re-

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structuring of firms. Fourth, concomitant with these changes the economy faces increasing competition from imports and greater orientation toward exports.

One indicator of the degree of structural change is the shift in the (gross) composition of employment both among occupations and among industries. Using the 1970, 1980, and 1990 U.S. Census of Population Public use Samples, total employment in each of those years is composed by 267 occupations and 64 industries.[3] Using the Duncan and Duncan index (the absolute values of the change in the percentage of employment in each category summed across all occupations or all industries), we find evidence of rising turbulence in the labor market in the 1980s relative to the 1970s. The Duncan and Duncan index increased from 20.1 for the 1970s to 26.3 for the 1980s on the basis of employment by occupation and from 10.6 to 12.4 on the basis of employment by industry.

A popular argument is that with the shift to services, corporate restructuring, downsizing, and outsourcing, job shifts have resulted in lower wages for displaced workers. The anecdotal example is that high wage manufacturing workers have become “hamburger flippers” in fast-food establishments.[4]

In this paper, we study whether the increased change in employment composition that characterized the 1980s relative to the 1970s was also accompanied by greater change in terms of both occupation and industry of employment on the micro level. Moreover, we are also interested in whether job changes are associated with earnings losses and whether this has become more likely over time. To study these issues, we draw on data from the Panel Study of Income Dynamics (PSID).

Previous research on labor mobility has focused primarily on mobility between jobs (employers/firms) and on the relationship between job seniority and earnings and worker-firm matching. Relatively few studies have investigated occupational and industrial mobility. Furthermore, this literature has focused mainly on occupational choice and occupational attainment. Models of occupational choice have concentrated on new entrants to the labor markets in which education and family antecedents play a key role. Such studies include Robertson and Symons (1990), Orazem and Mattila (1986), Shaw (1986), Miller (1984), and Rosen (1972). These studies argue that the intensity of human capital investment in occupational skills varies across occupations and individuals, and their results generally show that individuals do appear to change occupations to maximize the present value of their investment.

However, in the literature, there are some exceptions that consider the determinants of occupational and industrial changes. Sicherman and Galor (1990) analyze theoretically and empirically occupational mobility in the U.S. by focusing on individual careers. They conclude that education helps to increase the probability of occupational upgrading. Harper (1995) focuses on occupational quits in Britain as opposed to occupational upgrading. He finds that young (as we do) and more educated (unlike us) individuals are more likely to change occupations.

Our main focus here is to investigate job changes between occupations and industries over time and by gender. Our main findings are that workers changed both occupation and industry of employment more frequently in the 1981–1993 period than in the 1969–1980 period and that occupational and industrial changes lead to reduced earnings but the effect has lessened over

[3] See Wolff (1996) for details on the classification schemes.

[4] For a review on displaced workers see Fallick (1996). His main conclusion is consistent with the view that earning losses of displaced workers are large and persistent. Carrington (1993), in particular, finds that wage losses are much larger for displaced workers who switch industries.

time instead of increasing. We also find that men tended to change occupation and/or industry more frequently than women did. Furthermore, male workers who earn more are less likely to change occupation or industry, and this is true in general for women. Older men change occupation and industry less frequently but this tendency has declined over time. Finally, more educated workers tend to stay in the same occupation or industry, but, again, this effect has lessened over time.

A related concern of our paper is the relationship between job tenure and occupational and industry switching. Theoretical and empirical studies of wage determination growing out of job-matching models have established that job changes slow down over time with job tenure.[5] These models deduce a positive correlation between wages and job tenure even if wages do not grow as seniority increases. This is explained if match quality is job specific; in other words, individuals are less likely to quit and less likely to be laid off or fired as job seniority increases. Thus, job tenure and wages are positively associated with one another even with no increase in wage offers. Specifically, the disturbance term in the basic wage equation is positively correlated with job tenure. As Abraham and Farber (1987) point out, this may be explained by the correlation of tenure with an omitted variable representing the quality of the worker-job or worker-employer match.

Similarly, human capital models (for example, Becker, 1962) predict a negative relation between job mobility and tenure. Borjas (1981) and Mincer and Jovanovic (1981) analyze the relationships among job tenure, wages, and inter-firm labor mobility that depend on investment in job specific human capital. They find a strong association between job tenure and wages, a result they attribute to the firm-specific component of wages rising over time within the firm. In contrast with these results, Neal (1995), using the Displaced Worker Surveys (DWS),[6] shows that workers receive compensation for skills that are specific to their industry rather than completely general or firm-specific. Similarly, Parent (2000) and Neal (1999), using the National Longitudinal Survey of Youth (NLSY),[7] show that industry-specific human capital (rather than firm-specific) is what matters the most for the workers' wage profile. This would suggest that job matching is not only the process of finding a job match given a fixed career choice, but also the process of finding a good occupation/industry match.

The paper is organized as follows. Section 2 contains a description of our data and the methodology. Section 3 presents descriptive statistics. Section 4 reports the model specifications and discusses estimation issues. The final section summarizes the results and their implications for models of occupational and industrial changes.

2. Data sources and methods

The data for this study have been drawn from the Panel Study of Income Dynamics (PSID). The panel contains data for 26 years, from 1968 to 1993, which is the last year of the fully processed data available at the time this study was started. When coding occupations, one-digit codes in 1968–75, two-digit codes in 1976–80 and three-digit codes after 1981 were used. For

[5] See Jovanovic (1979) for a formal model of job matching and Light and McGarry (1998), Garen (1989), Abraham and Farber (1987), and Altonji and Shakotko (1987) for empirical tests of the job-matching model.

[6] In January of 1984, 1986, 1988, and 1990, the monthly Current Population Survey included a supplement with information from workers who had previously suffered a job displacement.

[7] Each individual work history covers the time period January 1978–December 1991.

coding industry classifications, two-digit codes were used in 1971–80 and three-digit codes were used after 1980.[8]

The PSID released the 1968–1980 Retrospective Occupation-Industry Files in 1999 (PSID, 1999). The aim of these files is to provide three-digit occupation and industry codes from 1968 to 1980. To recode occupation and industry affiliations, original paper records that contained the respondents' descriptions of their occupations and industries were used (the same records that were used to generate the original one-digit and two-digit codes). "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" (PSID, 1999). This allowed the coder to compare through years, past and future, the occupation and industry descriptions of the respondents, thus helped reduce errors that involved coding two similar descriptions differently. In the original files, the coder did not have the opportunity to see the previous years' descriptions.

We have to mention that the new files contain occupation and industry codes only for selected PSID heads and wives. There are two selection criteria: Being an original sample[9] head or wife still living by 1992 who reported main jobs in at least three waves during the period 1968–1992, with at least one of those reports prior to 1980; or being an original sample head or wife who had reported at least one main job between 1968 and 1980 but were known to have died by 1992. In other words, the selection criteria did not include all heads and wives who had worked between 1968 and 1980. Those who were still living but had reported only one or two jobs during the period of interest were excluded, as were all non-sample heads and wives (PSID, 1999). Table 1 shows how restrictive these selection criteria are. Both columns show the sample sizes for each year when samples are restricted to heads of households that satisfy the PSID selection criteria described above as well as our own criteria described later in the paper. In column (1), the observations for which the original occupation and industry codes are available (i.e. non-missing) are chosen. In column (2), both the original and the new codes are required to be available. As the table shows clearly, the additional criterion is not very restrictive in the first few years but becomes more restrictive towards the end of the 1970s.

For the 1969–1980 period, it is possible (as indeed shown later in this paper and by Kambourov and Manovskii, 2004) that the two series of occupation and industry codes generate different pictures of absolute mobility; partly due to the presumed coding error in the original files and partly due to the sample selection rules imposed during the construction of the retrospective files. For this reason, we restrict our attention to the individuals for whom both the original and the new (retrospective) codes are available. Using these samples, we present results for both the original and the new occupation and industry codes for this period. To minimize the effect of coding error on our estimates, we employ a very broad classification of occupation and industry categories, one that is very similar to the one-digit codes used by the PSID.

The following occupational categories are used in the study:

1. Professional, Technical, and Kindred Workers;
2. Managers and Administrators, Except Farm;
3. Clerical, Sales Workers and Kindred Workers;
4. Craftsmen, Foremen and Kindred Workers;
5. Operatives, and Kindred Workers;

[8] Industry codes were first recorded in the PSID in 1971.

[9] This 1968 sample consisted of a cross-sectional national sample and a national sample of low-income families (PSID, 1999).

Table 1
The effect of selection criteria of the retrospective occupation and industry files on sample sizes

Year	Original codes	Original and restrospective codes (2)	Effect of selection criteria (%)
	(1)	(2)	(2)/(1)
1969	1995	1903	95.4
1970	2071	1990	96.1
1971	1907	1805	94.7
1972	1916	1771	92.4
1973	1932	1730	89.5
1974	1693	1484	87.7
1975	1631	1404	86.1
1976	1682	1397	83.1
1977	1799	1455	80.9
1978	1893	1482	78.3
1979	1931	1485	76.9
1980	1900	1466	77.2

Source: PSID and authors' calculations.

6. Laborers and Service Workers, Farm Labor;
7. Farmers and Farm Managers; and
8. Miscellaneous (armed services, protective services, etc.).

The industry categories include:

1. Agriculture, Forestry, and Fisheries;
2. Mining;
3. Construction;
4. Manufacturing;
5. Transportation, Communications, and other;
6. Wholesale and Retail Trade;
7. Finance, Insurance, and Real Estate;
8. Business and Repair Services;
9. Personal Services;
10. Entertainment and Recreation Services; and
11. Professional and Related Services.

The samples are restricted to individuals who participated in the survey in at least one year and who met the following criteria: (1) heads of households or wives over 25 years of age; (2) those who were employed or on temporary layoff at the time of the interview; and (3) those who worked at least 1000 hours per year and reported being employed in an assigned occupation and industry. People who were self-employed in any year of the survey are excluded to focus the analysis on wage and salary workers. We also discard from the sample workers employed in the government. Based on these criteria the original sample was reduced to 11,135 men and 6937 women for the 1969–80 sample using the original files; 14,295 men and 8429 women for the same period using the new retrospective occupation and industry files; and 24,121 men and 16,649 women for the 1981–1993 sample. Deleting observations with missing values on tenure and experience variables and industry codes gives us slightly smaller samples (see Tables that show the results of our regressions analyses for specific sample sizes).

Variables collected for all samples include occupation of employment, industry of employment, real wages (hourly labor income), experience, tenure, marital status, education, race, age, and sizes of industry and occupation categories that the person is employed in. Wages in each year are deflated by the Consumer Price Index (using 1990 as the base year).

Our main focus is to measure and analyze occupation and industry changes on the basis of aggregate occupation and industry categories. In order to do that, we define occupational and industrial changes as the worker's shift from one aggregate occupation and/or industry to another, without unemployment interruptions. Therefore we exclude exits from and entries into the labor force. As in Sicherman and Galor (1990), we assume that occupational change will be observed if there is a dramatic shift in the tasks performed by the worker.[10]

A number of caveats are in order. First, our research does not take into account differences between voluntary and involuntary changes, because the missing data on the variable "what happened to previous job" in the first years of our sample are both frequent and very likely biased.[11] Second, we cannot distinguish between job changes between occupations and industries that are permanent and those in which workers switch jobs temporarily and then switch back to their previous occupation and/or industry within the year. Finally, changes in occupation may or may not be accompanied by a job switch to a new firm. On the other hand, a change in industry would also be associated with a change in firm of employment as well.

A few words should also be said about the differences between our paper and that of Kambourov and Manovskii (2004). While the two papers use the same dataset and analyze the same period, the Kambourov–Manovskii (KM) paper is very different from ours in its technique.

Before clarifying the relationship of our paper to the KM paper, it is helpful to present some more background information: As mentioned before, the Retrospective Files were generated by pulling out paper materials from the archives and re-coded occupations and industries, based on the written records of the respondents' descriptions of their occupations and industries. These files that were released in 1999 contain three-digit codes for the 1968–80 period.

The advantage of using the Retrospective Files is that they are prone to lower measurement error, as described above. The disadvantage is the length of the covered period. If one is interested in the post-1980 period, the original files are the only source of information. Another disadvantage is that the files do not include codes for all household heads and wives but only for those who satisfy some restrictions.

Thus, for a researcher there are three alternatives: The first is to use the original files for the entire 1968–93 period. We know that the codes in the pre-1980 period contain measurement error; however we have no idea about how reliable the codes in the post-1980 period are. We can only presume that the degree of error remained the same throughout time.

The second alternative is to use the codes in the Retrospective Files for the pre-1980 period and the original codes for the post-1980 period. The handicap here is the break in the series. Obviously, the data in the two sub-periods are generated using different methodologies. KM choose this alternative and make adjustments on the post-1980 period data with an effort to correct for the measurement error and make the two sub-periods comparable.

[10] An individual can change occupation and/or industry for many reasons, entailing either pecuniary or non-pecuniary causes. Such a decision may be elicited by the accumulation of new skills that bring future benefits, promotion, or higher wages, or the desire to improve job satisfaction, responsibility, or status. Job changes also result from involuntary job termination. Involuntary job changes might have different reasons. However, the PSID data does not allow to distinguish between voluntary and involuntary job changes.

[11] In contrast, the Displaced Worker Surveys (DWS) contain information from workers about both voluntary and involuntary job displacements.

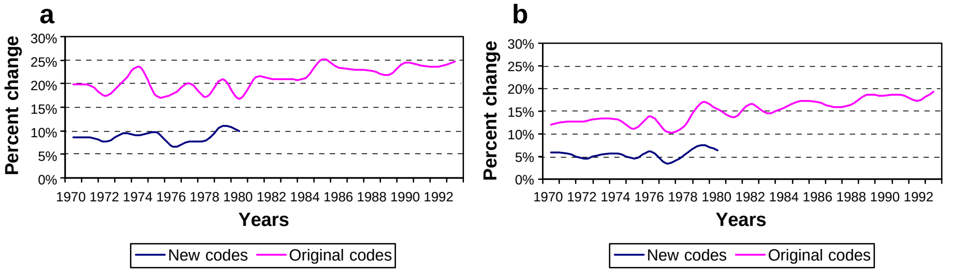

Fig. 1. a. Occupational mobility, men, 1969–1993. b. Occupational mobility, women, 1969–1993. Source: PSID and authors' calculations.

The third alternative is to use all available data; the original files for the entire 1968–93 period and the Retrospective Files for the pre-1980 period. This is the alternative that we choose to follow.

KM solve the "break" problem as follows: They use a probit model to estimate the probability of switching occupation (or industry). Among the independent variables is a "Break" variable that takes the value of one if the year is in the 1981–1993 period. The model coefficients are estimated based on the entire 1968–93 period data. Then these coefficients are used to predict what one's mobility would have been in each year after 1980 if there were no break by setting the coefficient on "Break" to zero. Using these "corrected" data, the authors present some descriptive results; namely the mobility rates, both for the entire sample as well as for some age-education groups.

In contrast to KM, we choose to use all available data. We do not make any adjustments or corrections to the data, because we can not be sure that the corrections will not introduce any further error. In order to be able to compare the different data, we restrict our attention to the individuals for whom both the original and the new (retrospective) codes are available. Using these samples, we present descriptive and analytical results for both the original and the new occupation and industry codes. To minimize the effect of coding error on our estimates, we employ a very broad classification of occupation and industry categories, one that is very similar to the one-digit codes used by the PSID.

3. Descriptive statistics

3.1. Occupational changes

Occupational mobility is defined in this paper as the percentage of currently employed individuals who report a current occupation different from their most recent previous report of an occupation. Fig. 1a and b show occupational mobility of men and women for the periods 1969–80 and 1981–93. Both the original and the new versions of the occupation data are used.

Both figures show slightly greater mobility of workers in the later period than the earlier one.[12] For men, occupational mobility ranged between 15 to 20 percent during the former period, with the exception of 1974 (which seems excessive), and between 20 to 25 percent

[12] These results are consistent with studies by Hall (1982), Ureta (1992), Swinnerton and Wial (1995), and Allen et al. (1993), who argue that jobs in the U.S. are becoming less stable and that long-term employment relationship are becoming less important.

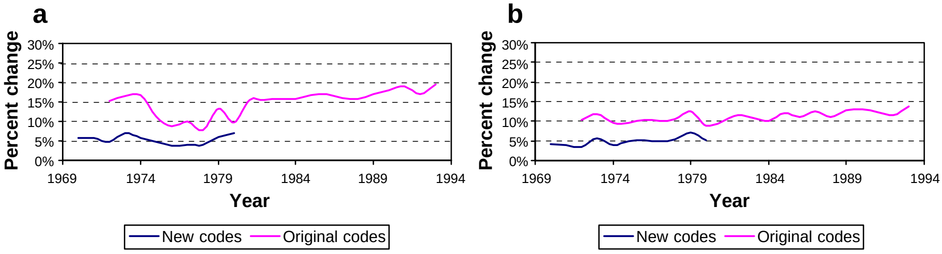

Fig. 2. a. Industrial Mobility, men, 1969–1993. b. Industrial mobility, women, 1969–1993. Source: PSID and authors' calculations.

during the later period according to the original occupation codes.[13] The new codes show that mobility ranged between 7 to 11 percent, which is lower than what is indicated by the original codes.[14] Mobility appears to be lower for women; it varied in the 10 to 15 percent interval during the former period, with a peak in 1979, and in the 15 to 20 percent interval in the later period. Once again, the original codes show higher mobility.[15]

3.2. Industrial changes

Fig. 2a and b show industrial mobility, defined in a similar way to occupational mobility, for men and women, for the periods 1969–80 and 1981–93.

Industrial mobility for men appears to have somewhat increased. Although it runs above 15 percent until 1974, in the second half of the 1970s it declines to around 10 percent. In the 1981–93 period, it varies between 15 to 20 percent. The new codes reveal a lower level of mobility, which is around 5 percent. For women, an increase in industrial mobility is less visible. As in the case of occupational mobility, industrial mobility is lower for women than for men. Once again, the new codes show lower mobility rates.

It appears that both the original and the new occupation and industry codes follow a similar rise and fall pattern. This is especially true for the mobility of women. As for the comparison of mobility patterns in the 1969–80 period to the 1981–93 period, there is no way of telling what the new codes would show, since the only data available for both periods are based on the original codes. Assuming that the degree of coding error in the latter period is similar to the one in the former period, one can only speculate that the new codes will show lower mobility than the original codes for the latter period.[16]

[13] Sommers and Eck (1977) report that 39 percent of adult men changed their 3-digit occupation at least once between 1965 and 1970.

[14] These observations are in line with the findings of Kambourov and Manovskii (2004).

[15] The mode number of occupational changes is around 2 for both men and women and for each time period. The distribution of number of changes tails off very quickly, with only about 20 percent of workers experiencing more than 3 occupational changes over each period.

[16] The new occupation and industry files (the Retrospective Files) contain codes for most but not for all household heads and wives. The re-coding procedure was performed if the respondent was an original sample head or wife satisfying some additional restrictions. Therefore, it should be noted that the sample in the 1968–1980 retrospective files gets older over time. (The mobility figures of the respondents in this sample are shown by the lower "New codes" line in Figs. 1 and 2.) We would expect it to bias the unadjusted trend for the 1968–1980 period towards a decline in mobility. However, the comparison of the before-1980 period with the after-1980 period is obviously not affected by the sample aging.

Table 2
Average change in real labor earnings by changes in occupation and industry

		Men			Women		
		1969–1980		1981–1993	1969–1980		1981–1993
		Retro	Original		Retro	Original	
Occupation	Change	9.2	8.9	9.7	13.9	10.0	14.0
		53.8	*51.5*	*65.6*	*55.0*	*47.6*	*85.4*
	No change	6.7	6.4	10.0	9.5	9.7	10.7
		52.8	*53.2*	*96.1*	*49.7*	*50.3*	*62.3*
Industry	Change	16.0	10.2	12.2	18.4	15.7	14.5
		61.3	*49.2*	*82.0*	*77.8*	*69.7*	*75.4*
	No change	6.4	6.4	9.4	9.2	9.0	11.0
		52.3	*53.3*	*90.7*	*48.0*	*47.3*	*66.6*

Note: Standard deviations in italics.
Source: PSID and authors' calculations.

It is also interesting to note that changes, either between occupations or industries, tend to entail a move between occupations that are similar (for example, changes from professional workers to managers) or industries that are similar (for example, from one service sector to another service sector). Almost 90 percent of these changes were between occupations or industries that require "similar" skills.[17] This observation suggests that general and specific human capital play an important role in determining the new kind of work that is pursued.

3.3. Labor earnings

Table 2 presents means and standard deviations of annual percentage change in real hourly labor income[18] in the 1969–80 and 1981–93 periods. Results are reported separately for individuals who stayed in the same occupation and/or industry from one period to the next and for those who changed occupation and/or industry from their last reported occupation and/or industry category. Also, the results for both the original and the new codes are presented.

Our most striking result is that the growth of hourly earnings has been substantially larger for changers than for stayers. This is true for both men and women, for both periods and for both original and new codes. On the surface, at least, it appears that pecuniary motives are the main reason behind occupational or industry change. These findings are also in accord with those reported by Wilson and Green (1990), who conclude that there exists a strong positive correlation between occupational mobility and changes in real labor earnings, even after controlling for personal characteristics and firm-specific human capital.

Second, not only are there striking differences in the growth in average hourly earnings between changers and stayers, but there are also differences in their volatility, especially in the case of the earnings of women. For them, the variance in hourly income is much greater for changers than for stayers. This result is consistent with the view that changing occupation and/or industry is a risky act but may have other causes as well. By contrast, for men, the variation in the earnings of stayers is noticeably higher than changers in the 1981–93 period.

[17] An example of a skill-related industrial change would be a shift from mining (category 2) to construction (category 3), while a shift from mining to entertainment and recreation services (category 10) would not qualify as a skill-related industrial change.
[18] Income figures are converted to 1990 dollars using the consumer price index (CPI-U).

Table 3
Average age by changes in occupation and industry

		Men			Women		
		1969–1980		1981–1993	1969–1980		1981–1993
		Retro	Original		Retro	Original	
Occupation	Change	36.5	39.6	36.6	37.0	39.9	37.8
		10.0	*11.1*	*9.7*	*10.3*	*10.7*	*10.3*
	No change	41.6	41.5	38.4	42.1	42.2	38.6
		11.0	*10.9*	*10.0*	*11.1*	*11.1*	*10.2*
Industry	Change	35.6	38.8	36.6	37.3	39.3	37.0
		9.7	*11.0*	*9.7*	*9.7*	*10.3*	*9.9*
	No change	41.4	41.5	38.2	42.1	42.2	38.7
		11.0	*11.0*	*10.0*	*11.1*	*11.1*	*10.2*

Note: Standard deviations in italics.
Source: PSID and authors' calculations.

Third, during the 1981–93 period, women registered higher increases in real labor income than men did. This observation is partially consistent with the finding of Becker and Lindsay (1994) that women experience more rapid job earnings growth than men do.[19]

Fourth, in the 1969–80 period, the original and the new codes yield similar findings in general. The exceptions are for women who change occupation or industry and for men who change industry.

3.4. Age

Are younger people inclined to change occupation and/or industry more frequently than older people? Results from Table 3 confirm this by showing that changers are, on average, younger than stayers,[20] although this difference is not statistically significant. This is true both for the original and the new codes. The age difference between changers and stayers is greater when we employ the new occupation and industry codes. In terms of volatility we do not observe a clear pattern.

One plausible explanation for this set of results is the fact that younger people have not accumulated general and/or specific human capital, which would diminish the risk of changing occupation or industry. Another possible reason is that education and job training generally occur when a person is young. The resulting general human capital makes it easier for workers to switch occupation or industry. Other explanations may reflect lower adjustment costs of changing, lower match quality due to less previous job search, and more learning about talents.

3.5. Education

Since the coding of educational attainment was not consistent through time in the PSID,[21] we recoded this variable to assign individuals to one of the following four educational categories:

[19] They used ordinary least squares to estimate earnings equations over the period 1981 through 1987.

[20] Markey and Parks (1989), using the January 1987 Current Population Survey (CPS), find that age is the principal factor in determining occupational mobility. They conclude that high mobility rates of young workers contrast with low rates among middle age and older workers.

[21] In some years the number of years of schooling was recorded whereas in some other years educational attainment was kept as a categorical variable.

Table 4
Average level of education by changes in occupation and industry 1/

		Men			Women		
		1969–1980		1981–1993	1969–1980		1981–1993
		Retro	Original		Retro	Original	
Occupation	Change	1.9	1.8	2.4	2.0	2.0	2.4
		1.0	*1.0*	*1.1*	*0.8*	*0.8*	*1.0*
	No change	2.1	2.1	2.4	2.0	2.0	2.3
		1.1	*1.1*	*1.2*	*1.0*	*1.0*	*1.0*
Industry	Change	1.9	2.0	2.4	2.0	1.9	2.3
		1.0	*1.1*	*1.1*	*0.9*	*0.8*	*0.9*
	No change	2.1	2.1	2.4	2.0	2.0	2.3
		1.1	*1.1*	*1.1*	*1.0*	*1.0*	*1.0*

Notes: 1/ 1: Less than high school degree, 2: High school graduate, 3: some college, 4, college graduate. Standard deviations in italics.
Source: PSID and authors' calculations.

less than high school degree, high school graduate, some college experience and college graduate or more.

Table 4 shows that in terms of educational attainment, changers and stayers are not very different in the 1981–93 period. In the earlier period, however, men who change occupation and industry appear to have less education, according to both the original and the new codes. Table 4 also reveals that average schooling among workers was higher in the later period than the earlier one, while the variance was lower. No substantial differences between men and women are found.

4. Model specification and estimation issues

Our estimation proceeds in two stages. The first is concerned with the determinants of occupational and industrial change. For this we use a logit regression where the dependent variable is a dummy variable with a value of one if a worker remains in the same occupation (or industry) category as the one reported previously. The second stage examines the effects of occupational (or industrial) change on earnings. For this we use a standard earnings function together with a variable indicating whether the worker changed occupation (or industry). The means and standard deviations of the variables used in these regressions are shown in Table 5.

This table confirms that the gender wage gap (in logs) has diminished over time. Women's wages rose from 82 percent of men's wages in the 1969–80 period to 85 percent in the 1981–93 period.

4.1. Logit estimation

In this section we present our first set of estimates. At each period an individual may be in one of two states. Let no change of occupation or industry be denoted by value *1*, and a change by value *0*. Let the value of being in state j be given by

$$V_{it}^{j} = \alpha + \beta X_{it} + u_i + \varepsilon_{it}, \quad j = 0, 1, \tag{1}$$

where matrix X_{it} includes real wages, age, age squared, educational attainment (the four categories mentioned before), marital status (1 if married, 0 if not), race (1 if white, 0 if

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Table 5
Descriptive statistics by gender and sample

	Men			Women		
	1969–1980		1981–1993	1969–1980		1981–1993
	Retro	Original		Retro	Original	
Education	2.02	2.05	2.40	1.89	1.90	2.29
	1.12	*1.11*	*1.14*	*0.95*	*0.93*	*0.97*
Experience	23.78	23.43	19.58	25.37	24.78	20.21
	11.93	*12.05*	*10.84*	*12.52*	*12.63*	*11.08*
Tenure	7.29	7.12	8.11	5.82	5.77	6.35
	7.67	*7.79*	*7.94*	*6.51*	*6.57*	*6.02*
Age	41.01	40.76	37.94	42.56	42.08	38.48
	10.83	*10.89*	*9.96*	*11.47*	*11.57*	*10.21*
Married	0.90	0.89	0.86	0.25	0.30	0.68
	0.30	*0.32*	*0.35*	*0.43*	*0.46*	*0.46*
White	0.68	0.69	0.67	0.53	0.54	0.59
	0.47	*0.46*	*0.47*	*0.50*	*0.50*	*0.49*
ΔOccupation	0.09	0.19	0.25	0.06	0.12	0.20
	0.28	*0.39*	*0.44*	*0.23*	*0.32*	*0.40*
ΔIndustry	0.06	0.13	0.17	0.05	0.10	0.12
	0.23	*0.33*	*0.37*	*0.22*	*0.30*	*0.32*
Size of Occupation	70.87	58.76	71.24	61.38	56.13	62.14
	29.65	*35.57*	*31.23*	*23.14*	*43.46*	*27.81*
Size of Industry	45.79	46.52	46.24	37.24	38.48	38.25
	33.06	*33.14*	*32.57*	*28.57*	*28.94*	*29.15*
Ln (hourly wage)	2.57	2.59	2.58	2.08	2.10	2.19
	0.53	*0.54*	*0.56*	*0.51*	*0.50*	*0.52*

Note: Standard deviations are shown in italics.
Source: PSID and authors' calculations.

nonwhite) and the size of the occupation or industry category (i.e. the number of 3-digit occupation or industry categories that exist within the much broader categories that we use). The residual structure in the equation includes an unobserved time-invariant individual characteristic term, u_i, and a white noise term $_{it}$ that captures all other unobserved variables. Each component of the residual is assumed to be independently distributed with zero mean and variance equal to σ_u^2 and σ^2, respectively.

4.1.1. Occupational changes

Table 6 reports the estimation results of the logit regression where the binary variable (change/no change) is the dependent variable. For the 1969–80 period, results are shown for both the original and the retrospective occupation codes. We notice that in general coefficient estimates carry the same sign in both cases. We find, first, that men with higher wages are significantly more likely to stay in the same occupation than men with lower wages. This is also true for women in the 1969–80 period (based on the new occupation codes) but not for the other two regressions where the estimates take different signs and are not statistically significant.

Second, older workers are significantly more likely to remain in the same occupation than younger workers and the effect is statistically significant in most samples. This result is consistent with those reported by Harper (1995) for Britain and with Shaw's (1986) model, which predicts that younger people are more likely to change occupations and that this

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Table 6
Panel data logit estimates of the probability of remaining in the same occupation from one-year to the next

	Men			Women		
	1969–1980		1981–1993	1969–1980		1981–1993
	Retro	Original		Retro	Original	
Constant	−2.103	−2.323	−1.167	−0.125	2.021	1.630
	0.001	*0.000*	*0.001*	*0.897*	*0.013*	*0.003*
Ln (real wage)	0.722	0.395	0.329	0.374	−0.130	0.044
	0.000	*0.000*	*0.000*	*0.003*	*0.235*	*0.533*
Age	0.067	0.084	0.048	0.077	0.025	0.025
	0.031	*0.000*	*0.006*	*0.099*	*0.518*	*0.341*
Age squared	−0.0001	−0.001	−0.0003	−0.0002	−0.00001	−0.0001
	0.716	*0.018*	*0.122*	*0.688*	*0.986*	*0.722*
Education	0.101	0.279	0.010	0.052	0.118	−0.106
	0.039	*0.000*	*0.690*	*0.529*	*0.092*	*0.017*
Married	0.295	0.119	0.158	0.308	−0.340	0.123
	0.013	*0.227*	*0.012*	*0.023*	*0.005*	*0.124*
White	−0.168	0.055	0.055	−0.313	−0.128	−0.315
	0.111	*0.523*	*0.340*	*0.036*	*0.334*	*0.000*
Size of occupation	0.007	0.003	0.005	0.003	0.0002	0.001
	0.000	*0.001*	*0.000*	*0.273*	*0.896*	*0.537*
Chi-square	296.03	242.64	233.12	86.26	32.78	44.6
N	14,295	14,211	24,121	8429	8401	16,649
# groups	2629	2594	4757	2035	2033	3758

Note: p-values are reported in smaller font italics.
Source: PSID and authors' calculations.

probability will decline over time. The quadratic effect of age is detected in all samples, but the estimate is significant in only one sample (men, 1969–80, original codes).

Third, schooling has a positive effect (with the exception of the case of women for the 1981–93 period), i.e. those with higher educational attainment are more likely to stay in their current occupation. This result can perhaps be explained by two opposite effects of education on occupational mobility. More educated workers may have a greater chance of finding the "right" occupation at the beginning of their working career and thus be less likely to change later on. On the other hand, more educated workers have a larger stock of human capital (including general training) and therefore a wider range of tasks that they can perform, and may thus have better opportunities to switch occupation (or industry).

Fourth, marriage increases the probability of staying (except for women in the 1969–80 period, using the original codes).[22] Fifth, the findings regarding race are mixed. For men, the signs of the coefficient estimates depend on the sample and none of the estimates is statistically significant. For women, the effect is negative in all three samples and statistically significant in two samples - that is, white women are less likely than nonwhite women to stay in the same occupation. Sixth, as expected, the higher the number of 3-digit occupations included in our broader occupation category, the higher one's chances of staying in that category.

[22] The age and marriage effects found here are consistent with results on job mobility reported by Becker and Lindsay (1994), among others.

4.1.2. Industrial changes

Table 7 presents the logit estimates for industrial changes. The results are very similar to the occupational change regressions. Those with higher wages (men or women) are significantly more likely to stay in the same occupation. Older workers are more likely to stay in the same industry category and the quadratic effect is negative. The exception is the 1969–80 sample for women. The effect of educational attainment as a determinant of staying in the same industry is mixed. The effect is positive and significant in the 1969–80 sample for women, using the original codes. It is negative and significant in the 1981–93 sample for men. In other samples, although the estimates may take a positive sign, they are not statistically significant. Married workers are in general more likely to stay in the same industry. Whites are less likely to stay in the same industry than nonwhites, although the level of statistical significance of this effect is low in some samples. As in the case of occupational mobility, the higher the number of 3-digit industries included in our industry category, the higher one's chances of staying in that category.

4.2. Earnings regressions

Our basic model derives from the standard human capital model and is given by:

$$\ln(w_{it}) = c + \gamma Z_{it} + \mu_i + v_{it}, \tag{2}$$

where $\ln(w_{it})$ is the log of the hourly wages deflated by CPI for individual i in time t and Z_{it} is a standard set of regressors that includes educational attainment (the four categories mentioned before), experience and tenure in years, marital status (1 if married, 0 if not), race (1 if white, 0 if

Table 7
Panel data logit estimates of the probability of remaining in the same industry from one-year to the next

	Men			Women		
	1969–1980		1981–1993	1969–1980		1981–1993
	Retro	Original		Retro	Original	
Constant	−3.832	−2.569	−0.680	0.995	0.661	0.342
	0.000	*0.000*	*0.116*	*0.364*	*0.529*	*0.583*
Ln (real wage)	1.365	0.803	0.477	0.732	0.356	0.334
	0.000	*0.000*	*0.000*	*0.000*	*0.006*	*0.000*
Age	0.111	0.081	0.050	−0.030	−0.009	0.048
	0.004	*0.017*	*0.022*	*0.579*	*0.860*	*0.108*
Age squared	−0.0006	−0.001	−0.0004	0.0011	0.00068	0.0002
	0.202	*0.183*	*0.154*	*0.086*	*0.250*	*0.502*
Education	0.076	0.084	−0.060	0.078	0.228	0.004
	0.220	*0.125*	*0.072*	*0.377*	*0.012*	*0.940*
Married	0.533	0.190	0.083	0.297	−0.001	0.310
	0.000	*0.148*	*0.291*	*0.039*	*0.994*	*0.001*
White	−0.317	−0.181	−0.034	−0.068	−0.130	−0.119
	0.019	*0.146*	*0.655*	*0.666*	*0.425*	*0.223*
Size of industry	0.011	0.017	0.011	0.008	0.0162	0.008
	0.000	*0.000*	*0.000*	*0.001*	*0.000*	*0.000*
Chi-square	372.23	299.84	305.53	113.61	103.76	97.18
N	14,295	11,135	24,121	8429	6937	16,649
# groups	2629	2328	4757	2035	1874	3758

Note: p-values are reported in smaller font italics.
Source: PSID and authors' calculations.

nonwhite) and a binary variable that indicates change in occupation or industry (1 if change, 0 if no change). Experience and tenure squared are also included in the model. The experience terms are incorporated to capture wage growth due to investment in general human capital, while the tenure terms capture wage growth due to investment in specific human capital. The term c denotes the constant of the regression and γ is the vector of coefficients.

The residual structure in the equation includes an unobserved time-invariant individual characteristic term (μ_i) and a white noise term (v_{it}) that captures all other unobserved variables. Each component of the residual is assumed to be independently distributed with zero mean and variance equal to σ_μ^2 and σ_v^2, respectively. This structure is consistent with the mover-stayer model (the argument is that personal characteristics induce high productivity workers to avoid job change and low productivity workers to undergo persistent job change).

The tenure variable refers to a position with an employer (firm) rather than to an occupational position with the same employer.[23] As documented in Brown and Light (1992), there are numerous inconsistencies in the PSID in reported tenure values. For example, an individual may report 3, 4.5 and 2 years of tenure in three consecutive years. To correct for these inconsistencies, they recommend partitioning the data into jobs and then re-defining the tenure variable accordingly. This ensures internal consistency. The problem is that the PSID does not explicitly identify employers. Therefore we have to rely on the relationship between reported tenure and calendar time to infer when employer changes occur. In this study, in assigning individual observations to jobs, we assumed that a job is being seen the first time whenever reported tenure is less than the elapsed time since the previous interview. This corresponds to “partition T” in Brown and Light (1992) and Parent (2000). In the above example, this rule tells us that the individual changed his/her job after the second year, i.e, we re-assigned the tenure values to 3, 4 and 1. Brown and Light (1992) find that this is a reasonable solution.

As many others point out (e.g. Altonji and Shakotko, 1987, and Light and McGarry, 1998), tenure is correlated with the error in the earnings equations. For example, tenure is likely to be correlated with μ_i because high productivity workers would receive higher wages and thus be less likely to quit. One can make similar arguments about the experience variable and the occupation/industry change indicator.

To avoid these problems we use an instrumental variables feasible generalized least square estimator (IV/FGLS). The instrumental variables for the tenure variables T_{it} and T_{it}^2 are the deviations of the tenure variables around their means for the sample observations.[24] These IV are uncorrelated by construction with the error component of the earnings equation. The instrumental variables for experience and occupation/industry change are defined similarly, but this time they are the deviations of these variables around their person-specific means.

We estimate Eq. (2) both by OLS and by IV/FGLS.[25] If the error component is specified as v_{it}, the model should be estimated by OLS, while if the error structure is specified as μ_i+v_{it}, the model should be estimated by IV/FGLS.

Tables 8 and 9 show the two sets of estimates for the earnings equation including a term for the occupational change indicator. Experience and tenure have the expected quadratic shape in

[23] Job tenure (the length of time an employee has been with an employer) has not been recorded in 1979 and 1980. For those years, information on the length of time spent at the present position is available. Also, in 1978 respondents over the age of 45 were not asked about their tenure with the current employer.

[24] If T_{it}^M is the mean of tenure for individual i over the sample observations in period t, we can define the instrumental variable T_{it}^V to be the deviation of T_{it} from the job mean - that is, $T_{it}^V=T_{it}-T_{it}^M$ and $(T_{it}^V)^2=T_{it}^2-(T_{it}^M)^2$.

[25] In some exercises, due to very poor model fit, we had to drop the experience and/or occupation/industry change variable from the instrument list.

Table 8
Estimates of earning equations including changes in occupation (OLS)

	Men			Women		
	1969–1980		1981–1993	1969–1980		1981–1993
	Retro	Original		Retro	Original	
Constant	2.057	2.049	1.912	2.010	1.979	0.693
	77.360	*76.890*	*96.560*	*43.590*	*43.020*	*71.430*
Education	0.183	0.182	0.203	0.163	0.164	0.217
	47.130	*46.730*	*70.310*	*19.510*	*19.600*	*54.520*
Married	0.150	0.153	0.108	−0.026	−0.028	−0.015
	11.990	*12.240*	*12.650*	*−1.640*	*−1.770*	*−1.980*
White	0.274	0.272	0.216	0.180	0.178	0.189
	31.900	*31.630*	*33.030*	*12.260*	*12.150*	*26.240*
Experience	0.031	0.031	0.019	0.007	0.008	0.012
	22.810	*22.880*	*16.280*	*3.120*	*3.430*	*9.190*
Experience^2/100	−0.006	−0.006	−0.004	−0.003	−0.003	−0.003
	−25.000	*−24.960*	*−17.180*	*−6.950*	*−7.140*	*−13.530*
Tenure	0.014	0.014	0.034	0.020	0.020	0.043
	14.470	*14.840*	*31.630*	*11.240*	*11.590*	*29.880*
Tenure^2/100	−0.002	−0.002	−0.005	−0.003	−0.003	−0.008
	−5.990	*−6.130*	*−14.060*	*−7.060*	*−7.260*	*−13.720*
ΔOccupation	−0.124	−0.064	−0.048	−0.086	0.074	0.002
	−9.270	*−6.640*	*−7.140*	*−2.960*	*3.540*	*0.200*
sigma sq v	0.189	0.190	0.207	0.194	0.194	0.191
N	13,626	13,626	23,987	4374	4374	16,547

Dependent variable: Log of wages.
Note: t-statistics are reported in smaller font italics.
Source: PSID and authors' calculations.

almost all regressions (with the exceptions of experience in the 1969–80 IV/FGLS regression for men and tenure in the 1981–93 IV/FGLS regression for women). In the OLS regressions, the returns to experience are smaller for women than for men, while the opposite is true for returns to tenure. In most cases these variables are highly significant. On the other hand, as is well known in the labor economics literature, tenure is positively correlated with individual and job characteristics and, therefore, OLS tenure estimates might be biased upward relative to estimates that take these characteristics into account. After we account for the correlation between tenure and the error component (individual effects) by using IV/FGLS, the coefficients for tenure decrease in most cases, and some become statistically indistinguishable from zero. Another interesting result is that in the OLS regressions, the slope of the wage-tenure curve is steeper for women than for men, but not in the IV/FGLS regressions.[26]

It is worth noting, as Becker and Lindsay (1994) argue, that high-wage jobs tend to be more permanent, creating a positive relationship between tenure and wages. However, they justify the use of OLS in estimating the earnings equation for three reasons. First, they argue that the bias is small, even for large and heterogeneous samples. Second, comparisons between groups with similar tenure status should give little scope for the bias to affect the coefficients associated with tenure. Third, there is no a priori reason to expect these biases to entail sex-specific effects; hence such a bias should not affect any kind of gender tests.

[26] Becker and Lindsay (1994) also find that the tenure slope is steeper for women than for men among workers who remain in the same job.

Table 9
Panel data estimates of earnings equations including changes in occupation (IV/FGLS)

	Men			Women		
	1969–1980		1981–1993	1969–1980		1981–1993
	Retro 1/	Original 1/	1/	Retro 2/	Original 2/	1/
Constant	3.124	2.025	1.680	1.626	1.619	0.560
	11.440	*16.430*	*51.710*	*33.420*	*33.500*	*4.840*
Education	0.057	0.028	0.135	0.159	0.160	0.263
	3.300	*1.880*	*24.870*	*13.130*	*13.280*	*28.560*
Married	0.002	−0.025	0.053	0.013	0.013	−0.031
	0.080	*−1.110*	*6.130*	*0.610*	*0.620*	*−2.800*
White	0.181	0.062	0.119	0.168	0.167	0.155
	3.650	*1.030*	*10.950*	*7.260*	*7.310*	*14.850*
Experience	−0.100	0.008	0.027	0.002	0.002	0.096
	−2.960	*0.550*	*7.250*	*0.670*	*0.760*	*8.690*
Experience^2/100	0.022	0.001	−0.005	−0.001	−0.001	−0.019
	3.610	*0.340*	*−6.790*	*−1.930*	*−2.010*	*−9.090*
Tenure	−0.027	0.046	0.025	0.017	0.017	−0.006
	−0.640	*1.180*	*3.370*	*3.550*	*3.510*	*−0.440*
Tenure^2/100	0.008	−0.013	−0.006	−0.003	−0.003	0.008
	0.650	*−1.160*	*−2.370*	*−3.310*	*−3.270*	*1.730*
ΔOccupation	−0.031	−0.022	−0.013	−0.031	0.009	−0.001
	−1.640	*−3.180*	*−2.790*	*−1.490*	*0.590*	*−0.160*
sigma sq u	0.146	0.146	0.165	0.138	0.138	0.142
sigma sq v	0.048	0.048	0.065	0.053	0.053	0.061
N	13,626	13,626	23,987	4374	4374	16,547
# groups	2623	2623	5516	1492	1492	4290

Dependent variable: Log of wages.
Note: 1/ Tenure, experience, and occupational change were instrumented. 2/ Tenure and occupational change were instrumented. t-statistics are reported in smaller font italics.
Source: PSID and authors' calculations.

Both sets of results show that our key variable, ΔOccupation, is negatively related to wages for men. This means that men who change occupations have lower wages than men who do not. In absolute value, the IV/FGLS estimates for men are considerably smaller then the OLS estimates. This shows the importance of correcting for the correlation between tenure (or experience or occupational change) and the error component (individual effects) by using IV/FGLS. Another finding is that for men the earnings losses associated with occupational shifts declined between the 1969–80 period and the 1981–93 period. For women, the results are mixed, with the coefficient estimates taking different signs in different samples and regressions.

As mentioned before, we expect the retrospective codes to contain less error. Looking at how the coefficient estimates on the occupation change (ΔOccupation) variable are affected by the coding change, we notice that we obtain a stronger negative relationship between ΔOccupation and log hourly wages using the retrospective codes as opposed to using the original codes.

We find that schooling has the expected positive coefficient and is mostly highly significant in both sets of regressions. Moreover, as found in other studies, the return to education rose over time for both men and women. We find that the return to schooling in the IV/FGLS regressions is much lower than it is in the OLS regressions.

According to the OLS results, married men earn about 10–15 percent more than unmarried men, while the differential is much smaller in the IV/FGLS regressions. This variable has highly

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significant OLS estimates in all samples, but in the IV/FGLS regressions only one estimate is significant. In contrast to married men, married women appear to earn less than unmarried women, but the estimates are not highly significant. Racial differences in earnings are highly significant both among men and women. In the OLS regressions, the white-nonwhite gap in earnings exceeds 20 percent; using instruments for the variables mentioned above reduces the gap to some extent.

The results for industry changes are shown in Tables 10 and 11. Coefficient estimates and significance levels on the control variables in these regressions are remarkably similar to those for the occupation change regressions. In the 1969–80 male samples, the coefficient estimates for ΔIndustry are about twice that of the estimates for ΔOccupation; but the two estimates are much closer in the 1981–93 samples. For men, a change in industry is associated with smaller earnings in both periods and for both estimation techniques, though with both estimators the coefficient estimate is smaller (in absolute value) for the 1981–93 period than in the earlier period. In the case of women, the coefficient estimates are negative but insignificant for the earlier period (with one exception where it is significant) in both estimation techniques but positive and insignificant for the later period with both estimators.

Moreover, as in the occupation change regressions, schooling has a positive and highly significant effect. Likewise, according to the OLS regressions, married men earn 11 to 15 percent more than unmarried men and the coefficient is highly significant, while the differential is much smaller and less significant in the IV/FGLS regressions (and actually negative though insignificant in one case). Married women, on the other hand, appear to earn less than unmarried

Table 10
Estimates of earning equations including changes in industry (OLS)

	Men			Women		
	1969–1980		1981–1993	1969–1980		1981–1993
	Retro	Original		Retro	Original	
Constant	2.077	2.017	1.908	2.012	1.983	1.692
	78.490	*66.780*	*96.830*	*43.830*	*40.450*	*71.550*
Education	0.182	0.182	0.204	0.162	0.158	0.217
	47.110	*41.440*	*70.810*	*19.470*	*17.280*	*54.520*
Married	0.141	0.148	0.110	−0.026	−0.039	−0.015
	11.340	*10.750*	*12.800*	*−1.630*	*−2.390*	*−1.970*
White	0.274	0.259	0.216	0.178	0.167	0.189
	32.040	*26.180*	*33.120*	*12.180*	*10.620*	*26.260*
Experience	0.031	0.035	0.019	0.007	0.009	0.012
	22.740	*22.010*	*16.460*	*3.170*	*3.590*	*9.190*
Experience^2/100	−0.006	−0.007	−0.004	−0.003	−0.003	−0.003
	−24.970	*−23.500*	*−17.290*	*−7.030*	*−7.140*	*−13.530*
Tenure	0.013	0.014	0.033	0.020	0.022	0.043
	13.710	*13.300*	*30.970*	*11.060*	*11.480*	*29.820*
Tenure^2/100	−0.002	−0.002	−0.005	−0.003	−0.003	0.008
	−5.540	*−6.190*	*−13.720*	*−6.970*	*−7.580*	*−13.730*
ΔIndustry	−0.248	−0.138	−0.060	−0.137	−0.016	0.005
	−14.970	*−10.560*	*−7.540*	*−4.530*	*−0.680*	*0.450*
sigma sq v	0.187	0.192	0.207	0.194	0.191	0.191
N	13,626	10,482	23,987	4374	3683	16,547

Dependent variable: Log of wages.
Note: t-statistics are reported in smaller font italics.
Source: PSID and authors' calculations.

Table 11
Panel data estimates of earnings equations including changes in industry (IV/FGLS)

	Men			Women		
	1969–1980		1981–1993	1969–1980		1981–1993
	Retro 1/	Original 2/	3/	Retro 2/	Original 2/	3/
Constant	1.826	1.679	1.679	1.626	1.651	0.566
	13.450	*39.850*	*51.720*	*33.440*	*31.700*	*4.830*
Education	0.069	0.132	0.135	0.159	0.156	0.264
	2.270	*14.700*	*24.890*	*13.140*	*12.070*	*28.350*
Married	−0.046	0.031	0.053	0.013	−0.001	−0.030
	−0.870	*2.100*	*6.130*	*0.590*	*−0.060*	*−2.750*
White	0.267	0.305	0.119	0.167	0.159	0.155
	6.200	*16.140*	*10.890*	*7.260*	*6.580*	*14.980*
Experience	0.096	0.034	0.027	0.002	0.005	0.095
	0.960	*6.330*	*7.260*	*0.700*	*1.580*	*8.560*
Experience^2/100	−0.027	−0.006	−0.005	−0.001	−0.002	−0.019
	−0.950	*−7.320*	*−6.830*	*−1.960*	*−3.050*	*−8.960*
Tenure	0.001	−0.008	0.026	0.017	0.012	−0.006
	0.020	*−0.510*	*3.450*	*3.550*	*2.770*	*−0.460*
Tenure^2/100	0.001	0.003	−0.006	−0.003	−0.002	0.009
	0.120	*0.640*	*−2.440*	*−3.310*	*−2.710*	*1.760*
ΔIndustry	−0.134	−0.035	−0.026	−0.030	−0.022	0.005
	−2.700	*−3.010*	*−4.710*	*−1.350*	*−1.240*	*0.430*
sigma sq u	0.144	0.149	0.165	0.137	0.140	0.142
sigma sq v	0.048	0.047	0.065	0.053	0.051	0.061
N	13,626	10,482	23,987	4374	3683	16,547
# groups	2623	2323	5516	1492	1406	4290

Dependent variable: Log of wages.
Notes: 1/ Tenure was instrumented. 2/ Tenure and occupational change were instrumented. 3/ Tenure, experience, and occupational change were instrumented. t-statistics are reported in smaller font italics.
Source: PSID and authors' calculations.

women, but the estimates are not highly significant. Racial differences in earnings remain highly significant both among men and women and for both estimators. Likewise, when we use IV/FGLS instead of OLS, the coefficient of the tenure variable becomes smaller and less statistically significant.

5. Summary of findings

Two main findings come out of this study. First, the greater turbulence we found for the aggregate economy in the 1980s relative to the 1970s, as evidenced by the larger change in the (gross) distribution of employment both by occupation and industry, is echoed at the micro level. In particular, workers changed both occupation and industry more frequently in the 1981–93 period in comparison to the 1969–80 period. For example, occupational mobility for men ranged from 15 to 20 percent per year during the first period and from 20 to 25 percent per year over the second. We also find that men tended to change occupation and/or industry more frequently than women did.

Second, although the descriptive statistics indicate that occupation and industry changers had, on average, greater *unconditional* growth in earnings over these two periods than non-changers, we find that male workers who shift occupation or industry have lower earnings (*level*) than non-changers, once personal characteristics, such as schooling, work experience, job tenure, marital status, and race are controlled for. Moreover, despite all the horror stories in the press that manufacturing workers are turning into hamburger flippers, both occupational and industry change has become generally less traumatic over time, for men at least. In particular, while for men occupational and industrial changes are associated with lower earnings, this effect has lessened somewhat over time instead of increasing. In contrast, for women the results are mixed (and generally not statistically significant).

There are several other noteworthy findings. First, our results indicate that older and more educated workers change occupations and industry less frequently but this tendency has declined over time. Second, we find that schooling has the expected positive and significant effect on earnings, that married men earn more than unmarried men while in general the opposite is true among women, and that the racial earnings gap is of the order of 20 percent, once we control for other factors.

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