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ABSTRACT

Francs or Ranks? Earnings Mobility in France, 1967-1999*

This Paper uses a new dataset drawn from official earnings records kept by the French national statistical agency, INSEE, and builds a time series on various mobility indices for the first time. Using six mobility concepts, we chart wage mobility trends for the working population and compare mobility rates in various population subgroups differentiated by gender, and education. We then compare mobility trends over time for each population subgroup. Next, we relate the extent of mobility using each of these concepts to measures of macroeconomic conditions including GNP growth, unemployment, inflation, and change in the minimum wage. The results show that the answers to even the most fundamental of mobility questions depend on the mobility concept used. Specifically, we find: over time, income mobility in France has risen for some concepts and fallen for others; comparing genders, women have higher income mobility for some concepts and lower income mobility for others; looking across educational groups, it is the best-educated workers who have the highest mobility, while for other concepts, it is the least-educated; in general, the indices are affected by demographic variables, macroeconomic conditions, and changes in employment composition, but these patterns are not uniform across the different concepts; changes in ranks track only imperfectly changes in francs, and the relationships are far from linear. The implication is that before labour economists 'do a mobility study,' they need to be very clear about the mobility concept or concepts they wish to study. As our work shows, the choice can and does make a vital difference.

JEL Classification: J30
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1. Questions and Previous Literature

1.1. Our Questions and Contributions

In the international literature, most economic mobility studies work with transition matrices (Atkinson, Bourguignon, and Morrisson, 1992; Buchinsky and Hunt, 1999; Fields, 2001). Typically, the rows and columns of such matrices are quantiles (such as quintiles or deciles) of the base year and final year income distributions. Because quantile transition matrices are based on ranks in the income distribution, they can only present a picture of changes of position within the income distribution and cannot say anything about the changes in dollars or other currency units, either within or across quantiles.

The core question of this paper is, how similar are rank-based measures to currency-based measures (dollars, francs, euros, etc.)? We distinguish among six different mobility concepts, some based on positions in the income distribution and some based on currency units. These six concepts – time-independence, positional movement, share movement, income flux, directional income movement, and mobility as an equalizer or disequalizer of longer-term incomes – are discussed in detail in Section 2.

To what extent do these different concepts present the same qualitative picture or a different one? To the best of our knowledge, there is no published literature on this question for any country in the world. The closest is an unpublished paper by Fields, Leary, and Ok (2000) that was being prepared at the same time that this paper was. Fields, Leary, and Ok used data from the Panel Study of Income Dynamics to analyze changes over time in earnings mobility of U.S. men. They found that positional movement, share movement, income flux, and time-independence all exhibited inverted-U patterns over time. Directional income movement, however, was different, in that it *rose* over time. This pattern is in marked contrast to prior, rank-based studies; in the words of Gottschalk (1997): "Only a few studies have looked at changes in earnings mobility. Some have found declines, most have found no change, and none has found any increase."

The most important limitation of the PSID in the United States, and likewise of most other panel data sets in other countries, is the lack of independent verification of reported labor earnings or other income sources. To overcome this problem, in this study we use data for France. France is chosen because of exceptional data: administrative records on earnings over a period of thirty-two years. The data are discussed in Section 3. The fact that these are administrative records means that reporting error is entirely absent from our earnings measure. For no other country in the world is such information available for a nationally-representative sample of the working population.

We compare earnings mobility over time and for different groups in France and analyze reasons for these differences. The observed patterns in the French case are

presented in Sections 3 through 5. A statistical analysis follows in Sections 6 and 7. The main results are summarized in Section 8.

1.2. Previous Literature for France

There is now a fairly substantial literature on income mobility in France, nearly all of it limited to analysis of labor earnings. The earliest studies had only limited data bases. Baudelot (1982, 1983) used an early version of the Déclarations Annuelles de Salaires (DAS-DADS), the data that are used in our study, for a short period of time (1970-1975) and with very few personal characteristics of the workers. This study pioneered the use of quantile mobility matrices in France – in this case, a ventile (20 x 20) matrix. He showed that the greatest immobility was in the highest ventiles, as well as in the lowest one. Subsequently, in two papers, Bourguignon and Morrisson (1984, 1987) measured the wage mobility of a small sample of blue-collar workers and white-collar workers respectively, over a very long period of time (28 years, and even 39 years for a subsample). The decile mobility rate of managers (i.e., the percentage of managers who changed deciles) was found to range from 0.39 over a five year period up to 0.61 over a 27 year period, while for non-managers, the corresponding rates were 0.41 and 0.51 respectively. These authors also found less mobility in the extreme deciles of the wage distribution than in the middle, as was found in Baudelot (1982).

The next mobility research in France was a series of papers by Bigard, Guillotin, and co-authors. They also used the Déclarations Annuelles de Salaires (DAS), for a longer time period but also including a limited number of worker characteristics. In Guillotin and Bigard (1992), they presented a ventile mobility matrix derived from the DAS data for earnings changes from 1967 to 1992, from which they calculated various measures of dependence as well as various measures of movement. One finding of interest is that workers in the highest quartile of earnings in the base year had more ascending ventile jumps and fewer descending ventile jumps than would be predicted under perfect mobility, while the opposite was the case for those in the lowest quartile. In Bigard and Guillotin (1996), they traced earnings trajectories using the technique of "characteristic paths," i.e., identifying each individual's income quintile in each year from 1978 to 1988 and finding which sequences were most common. The most frequently observed paths, not surprisingly, were ones that involved no change of quintile at all (e.g., 11111111111) or ones that involved a single change (e.g., 45555555555). Later, Guillotin and Hamouche (1997, 1999) measured decile mobility over fourteen years (their 1997 study) and over nine years (their 1999 study) and found that by far the largest value was in the 10-10 decile, i.e., individuals who started in the highest earnings decile and remained in that category fourteen or nine years later. Bigard, Guillotin, and Lucifora (1998) compared earnings mobility in France and Italy over the same fourteen year period using a number of decile-based measures. France, they found, had greater

earnings mobility than Italy. Looking at mobility differences within France, they found greater earnings mobility in the central deciles of the earnings distribution than at the ends, higher earnings mobility when the economy is growing, similar mobility rates for men and women, greater upward mobility for the young, and greater downward mobility for the old. Note that all these studies were based on ventiles, deciles, or quartiles, and therefore all gauge the changes in position within the earnings distribution for French workers. (This is also true of Bigard, 1999, cited below).

Two other studies compared mobility rates for different groups in France. OECD (1996, 1997) examined earnings mobility from 1984 to 1989. Using quintile mobility matrices, the OECD studies showed higher immobility (i.e., less mobility) for men than for women, for workers 35 years of age and over than for younger workers, and for managerial, professional, and technical workers than for other occupation groups. In a later study, Bayet and Colin (1998) measured ten-year mobility, taking as their measure the complement of the correlation coefficient between earnings in 1982 and in 1992 . They too compared groups, but got somewhat different results from the OECD: a higher correlation coefficient for women than for men, for managers and employees than for manual workers, and for middle-aged workers than for young workers.

Both the OECD study and the Bayet-Colin study presented the distribution of earnings changes in francs. In the latter study, the authors reported that while the median real earnings change was plus eleven percent over a ten-year period, the fifth percentile of the earnings change distribution was minus twenty-three percent while the ninety-fifth percentile was plus seventy-nine percent. The OECD study also showed a wide dispersion of individual experiences. Furthermore, Bayet and Colin included a regression model of change in log-earnings, showing that only a small proportion of the evolution of individual earnings is explained by such personal and job characteristics as gender, age, occupation, economic sector, size and location of the establishment.

Three French studies examined changing income mobility over time. Buchinsky, Fougère, and Kramarz (1998) looked at two-year and five-year earnings mobility for periods beginning in 1967 and carrying through to 1987. They converted annualized earnings into ten deciles, plus an out of sample category (consisting of persons who were in the public sector, part time work, unpaid work, unemployed, or out of the labor force). Applying several different mobility measures to movement among these eleven groups (the measures used were the trace, Bartholomew's index, the extent of decile-leaving, and the determinant of the transition matrix), they found that both two-year mobility and five-year mobility fell over time. This was true for both men and women and for the least-educated. They also found that in each year, the highest decile exhibited lower mobility than other deciles. Another study of changing mobility over time in France was by Chambaz and Maurin (1996). They used data on household income category to estimate income changes between one year and the next. The correlation coefficients between estimated incomes in year t and t+1 were on the order of 0.85 with

no discernible trend. However, when the data were aggregated into quartiles and the observations grouped into periods, the authors found more interquartile mobility in the 1984-87 period than in 1987-89 or 1989-94. Most recently, Bigard (1999) studied the change over time in two-year wage mobility using several different positional movement measures (rank correlation, distributional change, mean absolute jump, Prais index, and immobility ratio). All of these measures exhibited falling wage mobility from 1968-70 to 1993-95.

Finally, we have in the OECD study (1996) international comparisons of earnings mobility in France vis-à-vis other OECD countries (the United States, United Kingdom, Denmark, Sweden, Germany, and Italy). France shows up consistently as a low mobility country. As gauged by the rate of quintile movement, France is at the bottom of the mobility scale. Using the correlation coefficient, only Italy and Germany are less mobile than France. And using measures based on median-proportion earnings bands, only Sweden is consistently below France in terms of mobility.

This completes our review of the previous literature on income mobility in France. In view of what has come before, the contributions of our study to knowledge about France are several. Using a newer and longer panel on annualized earnings of individual workers than was previously available for France (only Bigard (1999) uses data almost as recent as ours, but he lacks information on personal characteristics of the workers), we go beyond changes in positions and correlations over time. Using each of six economic mobility concepts - positional movement, time-dependence, share movement, income flux, directional income movement, and mobility as an income equalization - we chart income mobility trends for the working population and compare mobility in various population subgroups differentiated by gender, education, age, and base-year earnings decile. We then compare mobility trends over time for each population subgroup. We also relate the extent of mobility using each of the six concepts to measures of macroeconomic conditions including GNP growth, unemployment, composition effects, and change in the minimum wage. Finally, we try to understand the common structure of these six indices using a statistical model.

2. Six Mobility Notions

Any mobility index, because it is an index, summarizes aspects of the changes of individual earnings (or wages or income) across time. Indeed, if $f_{t,k}(w_{i,t}, w_{i,t+k})$ denotes the joint distribution of individual wages at dates t and $t+k$, there are many possible ways to construct mobility indices. Indeed, theorists have produced many such constructions, along with accompanying axioms that justify that precise index (see Shorrocks, 1978a; Sommers and Conlisk, 1979; Bartholomew, 1982; Geweke, Marshall, and Zarkin, 1986; Dardanoni, 1993; Fields and Ok, 1996 to cite just a few; see Fields and Ok, 1999 for a recent and very complete survey of the literature). As Fields and Ok (1999) note,

there is up to now no consensus view that emerges from this literature. This absence likely stems from the object itself, i.e., the analysis of the joint distribution of individual earnings measured at two dates, which is much more complex than inequality, which involves the analysis of the distribution of individual earnings at one date only.

If we adopt the perspective from Fields and Ok (1999), we are led to distinguish between various concepts when measuring earnings or wage mobility. First, it is possible to conceptualize mobility based either on *absolute* or *relative* mobility. In the latter, a scale invariance of some sort is assumed. The former type of index, by contrast, allows one to talk about mobility in terms of francs or dollars. Second, it is possible to conceptualize mobility based either on *structural* or *exchange* mobility. Exchange mobility focuses on changes in positions without changes in the underlying distributions of earnings. Structural mobility involves no such positional changes but examines the effects of changes in the distributions themselves. Third, it is possible to conceptualize mobility based on *transition mobility matrices* and, indeed, a large part of the theoretical as well as of the applied literature has focused on such indices.

Based on the above remarks, we consider six different concepts of earnings mobility; see also Fields (2001). *Time-dependence* measures the extent to which economic well-being in the past determines individuals' economic well-being at present. (Note that this is a measure of immobility, not mobility.) *Positional-movement* takes place when there is a change in individuals' economic positions (ranks, centiles, ventiles, deciles, or quintiles). *Share-movement* occurs when individuals' shares of total income change. Then, there is *income flux* which arises when individuals' incomes change and the analyst is concerned about the magnitude of these fluctuations but not their direction. Next, we have *directional income-movement,* in which income gains and income losses are treated separately. Finally, there is mobility as *equalization of longer-term incomes,* i.e., the extent to which mobility causes incomes over a longer period of time to be more equally distributed than incomes in the base year.

In what follows, we use the following notation. We let $x \longrightarrow y$ denote a matched pair of elements in R^n, where n denotes the number of individuals present in the base-year and in the final-year. A given element of such a pair is the movement of individual i from base-year earnings x_i to final-year earnings y_i, both measured in real francs. To avoid complications, we consider individuals for whom both x_i and y_i are observed in a given mobility period, e.g., 1997 to 1999.

Each of these six concepts has various indices associated with it. We turn now to the formal definitions of these mobility indices.

2.1. Time dependence/independence of earnings and of ranks

As mentioned above, *time-dependence* measures the extent to which economic well-being in the past determines individuals' economic well-being at present. There are at least

three measures of time-dependence:

a. Using a decile transition matrix, we can use the minus chi-squared statistic, defined as

$$-\chi^2 = -\sum_{i,j} \frac{(p_{i,j} - 0.1)^2}{0.1} \tag{1}$$

where p_{ij} denotes the probability of moving from decile i to decile j. We use minus chi-squared in place of ordinary chi-squared, so that the index rises when there is more mobility (time-independence).

b. The Pearson correlation coefficient between base-year earnings and final-year earnings, r, may also be used. Assuming the coefficient comes out positive, as it invariably does in empirical applications, a larger value signifies more positive time dependence. So to have a measure of mobility as opposed to immobility, one can use $1 - r$.

c. The coefficient of rank correlation between x_i and y_i, denoted ρ, is another possible measure of time-dependence. Likewise, assuming it comes out positive, a larger value signifies more positive time dependence. So to have a measure of mobility as opposed to immobility, one can use $1 - \rho$.

Minus chi-squared is the measure of mobility-as-time-independence used in this study.

2.2. Positional movement

Positional-movement takes place when there is a change in individuals' economic positions. Any such measure is therefore based on changes in ranks such as centiles, deciles, or quintiles. Commonly-used examples of such indices are the following:

a. The decile immobility ratio, which is computed as the fraction of people who remain in the same decile.

b. The per-capita decile movement, defined as:

$$\frac{\sum_i |dec(x_i) - dec(y_i)|}{n} \tag{2}$$

c. The per-capita centile movement, defined as:

$$\frac{\sum_i |cent(x_i) - cent(y_i)|}{n} \tag{3}$$

2.3. Share movement

Share-movement occurs when individuals' shares of total earnings change, regardless of whether their incomes or positions change. The resulting index is defined as the per-capita share movement, which is calculated as

$$\frac{\sum_i \left| \frac{x_i}{\overline{x}} - \frac{y_i}{\overline{y}} \right|}{n} \tag{4}$$

2.4. Earnings flux

Earnings flux indices try to measure the extent to which individuals' earnings change, taking into account the magnitude of these fluctuations but not their direction. Examples of such indices are:

a. The per-capita non-directional income change in logs:

$$\frac{\sum_i |\ln(x_i) - \ln(y_i)|}{n} \tag{5}$$

b. The per-capita non-directional income change in francs:

$$\frac{\sum_i |x_i - y_i|}{n} \tag{6}$$

2.5. Directional Earnings Change

Indeed, *directional earnings-movement*, in which earnings gains and losses are treated separately, gives rise to the following indices:

a. The per-capita directional earnings change in logs:

$$\frac{\sum_i (\ln y_i - \ln x_i)}{n} \tag{7}$$

b. The per-capita directional earnings change in francs:

$$\frac{\sum_i (y_i - x_i)}{n} \tag{8}$$

The latter index is a measure of growth of the economy, so we will not use it here.

2.6. Mobility as Equalization of Longer-Term Incomes

Finally, we will also examine *mobility as equalization*, i.e. the extent to which mobility causes earnings over the longer term to be more equally distributed than earnings in the base year. Two such indices have been proposed:

a. Shorrocks's M index, defined as

$$1 - \frac{I(x+y)}{[\mu(x)I(x) + \mu(y)I(y)]/\mu(x+y)} \tag{9}$$

where x is base-year earnings, y is final-year earnings, $\mu(.)$ is the mean earnings, and $I(.)$ is an index of inequality (Shorrocks, 1978b). The index of inequality that is used in this study is the Theil-L coefficient:

$$I = \sum_{i=1}^{n} \frac{1}{n} \log \left(\frac{\sum_n \frac{x_j}{n}}{x_i} \right) \tag{10}$$

for the origin period, where n denotes the number of individuals in the population of interest.[1]

b. Fields's equalization index, defined as

$$1 - \frac{I(x+y)}{I(x)} \tag{11}$$

(Fields, 1999). Here too, a possible index of inequality, indeed the one we use, is the Theil-L coefficient.

Our analysis will present this last index to assess mobility as equalization of longer term incomes.

3. Data and First Results

3.1. Data Description

The analysis in this paper is based on two-year mobility (i.e., changes in francs and in ranks between year t and year $t+2$) for 1967-69, 1968-70, ..., up to 1997-99, for a rolling

[1] For their analysis of wage mobility in the United States, Buchinsky and Hunt (1999) focus on two concepts of mobility: mobility as equalization of longer-term incomes (measured by Shorrocks's M index), and positional movements (measured by the average jump and by the mean reciprocal exit time in quintiles matrices).

panel of French workers. The data set used matches information from two data sources. The first one is the *Déclarations Annuelles de Salaires* (DAS, now called DADS, *Déclarations Annuelles de Données Sociales*), for the period 1967 to 1999, an administrative data set. Every year all French firms declare to the fiscal administration total earnings paid to each of their employees. The Income Tax Division (Division des Revenus) of the French national statistical office, INSEE (Institut National de la Statistique et des Etudes Economiques), receives these declarations and prepares an extract of the DAS-DADS for scientific analysis, covering all individuals employed in French enterprises in the private or semi-public sector who were born in October of even-numbered years, excluding civil servants. The latest available extract runs from 1967 through 1999, with 1981, 1983, and 1990 excluded because the underlying administrative data were not sampled in those years due to the 1982 and 1990 Censuses. Hence, the sampling rate is approximately equal to 1/25 of all French workers. For any such individual employed in any given firm, we know the total earnings paid by the firm, the number of days worked in that firm, and the full-time/part-time status of the person. As in Abowd, Kramarz, and Margolis (1999), we keep only the longest spell of employment and convert the earnings into annualized earnings using the number of paid days. Furthermore, we only keep full-time workers in our analysis sample since there is no measure of hours in the DAS-DADS.

The second data source, the *Echantillon Démographique Permanent* (EDP), also merges information from various sources: civil-status registers for births, marriages, divorces, and deaths and, more importantly for us, the various censuses (1968, 1975, 1982, and 1990). From the EDP, we use information on the sex, the date of birth, and the education level measured as the highest diploma obtained by each individual. We adopt the same diploma classification as in Abowd et al. (1999): the first group comprises all workers with no diploma; the second group comprises all workers with a certificat d'études primaires (CEP) or a BEPC (equivalent to junior-high school); the third group includes all workers with a technical diploma from high school (CAP or Brevet Professionnel); finally, the fourth group includes all workers who received their baccalauréat and spent some time in university. The EDP is a census of all persons born in the first four days of October of an even year. It is possible to match the two data sources using the common identifier present in the two data sources.

In fact, our analysis panel is the result of two sub-panels of the DADS-EDP that were independently constructed for the period 1967 to 1987 and for the period 1976 to 1999. To obtain a unique panel, we checked the consistency of the panels during the period that was common to the two sub-panels, 1976 to 1987. Most inconsistent records were eliminated, in particular, when an individual had some positive earnings between 1976 and 1987 in one of the two sub-panels but none in the other sub-panel. The resulting data set is an unbalanced panel that comprises 65,750 individuals with positive earnings in at least one year with age between 16 and 65 in that year. Roughly two-thirds of

these observations were males. Of the 65,750 individuals, 9,066 were present in exactly one year, 5,354 were present in exactly two years, 3,453 were present in exactly 5 years, and 512 were present for all 30 years, the maximum number of years possible.

Since our interest is in two-year mobility, we need to focus on workers with available earnings in years t and $t+2$. We restricted attention to those with positive earnings in at least one pair of years, t and $t+2$. Then, to protect ourselves from outliers, we eliminated all workers for whom the ratio of two consecutive annual earnings was either greater than 6 or smaller than 1/6. Consequently, our mobility indices were based on different sub-samples for each pair of years. The average sample consists of approximately 17,500 individuals, the smallest having 14,600 individuals in 1985-87 and the largest 20,281 in 1995-97. Earnings are measured in 1970 French francs.

3.2. First Results

The question asked in a typical mobility study, based on a quantile transition matrix is: Which are the most frequently-occurring cells? The answer for France, as for elsewhere, is that the most common are the (1,1) and (10,10) cells - that is, those who start in the poorest decile and those who start in the richest decile are the most likely not to change deciles (Fougère and Kramarz, 2001). Our data for 1967-99 show that too.

More generally, the transition matrix tells us the distribution of decile changes for those who start in any given decile - that is, it presents the information needed to gauge positional movement. This is one way to measure the extent of mobility or immobility in the labor market but not the only way. Instead, we can ask: How large is the earnings change measured in francs for those who start in each of the ten deciles? These can be measured algebraically or in absolute value. The mean change in francs (algebraic) informs us about upward and downward mobility, while the mean change in absolute value of francs informs us about income flux/variability. Both are interesting. These calculations for the most recent period (1997-1999) are presented in Table 1. This table presents three mobility indices for the entire population and for groups: absolute change in ranks (deciles), algebraic and absolute changes in francs. These results show that decile mobility, measured in absolute terms, is three-quarters of a decile. In (algebraic) francs, annual earnings increased by 1,390 francs whereas earnings flux amounted to 3,490 francs, almost three times the algebraic measure. Comparing mobility of various groups, we see that the most mobile based on the rank measure are the least mobile based on the francs measure (men versus women or low-education group versus high-education group). These results are not necessarily surprising since the deciles at the bottom of the distribution are narrower, in francs terms. Finally, results by decile in the base year demonstrate a roughly similar phenomenon when comparing francs and ranks in absolute values. In algebraic values, however, the results are less clear even though the bottom of the distribution seems to have benefitted from earnings mobility.

Another question commonly-asked in mobility studies is how mobility has changed over time. Of course, for the population as a whole, the mean change in ranks (algebraic) is zero, so we instead look at the mean change in absolute value of ranks. Results for the earliest period (1967-69) are presented in Table 2. The structure of the table is exactly similar to the previous one. In addition, when comparing the various groups, most results are close to those presented just above. However, comparisons across time are very instructive. Focusing on absolute changes in ranks and algebraic changes in francs, mobility has uniformly and strongly decreased. But, comparisons of earnings flux – absolute changes in francs – show a uniform increase: the end of the sample period displays more (earnings) instability.

Indeed, according to the first two indices, mobility in France is lower now than it was, but the two franc-based statistics tell us very different things. The comparison of the mean absolute value of change in ranks tells us that French workers are not changing as many positions in the earnings distribution as they used to. The comparison of mean change in francs tells us that French workers are not moving up as much in the earnings distribution as they used to. However, the comparison of mean absolute value change in francs tell us that French workers have more volatile incomes than they used to. All are interesting; very simply, they are different.

4. Comparing Mobility Over Time: Further Results

Figure 1 presents time paths of six earnings mobility indices, one for each concept, for the period 1967-69 to 1997-99. 95 percent confidence intervals are drawn, using an optimal number of bootstrapped replications.[2] In these and other figures, the starting year is indicated; hence, the points labeled 1967 correspond to mobility as measured between 1967 and 1969, and so on.

The six indices and the concepts they measure are listed in Table B.1 in the Appendix. Since the minus chi-square and the per-capita centile movement indices are constructed using deciles and centiles respectively, they fall within measures of rank movement. Clearly, the per-capita directional and non-directional log-earnings changes are franc-based. Finally, per-capita share movement and the Fields-Theil-L indices are both constructed using individual (level)-earnings measured in francs together with the average earnings in the economy. Hence, they are both (relative) franc indices.

Interestingly, five of our six mobility indices show similar trends with just minor differences. For these five indices (the Fields-Theil-L excepted), the first years (approximately 1967 to 1973) are years of stable or increasing mobility. The intermediate years (from 1971 to about 1977 or 1980) are years of sharply-decreasing mobility. Finally, the last period seems to show ups and downs with no clear trend, except maybe at the end

[2] Appendix A presents the bootstrap method used for the estimation of confidence intervals.

where mobility seems to be going up (except for the chi-square measure). All five of these indices show much lower mobility in recent years than earlier ones.

The one index that exhibits a different pattern is the Fields-Theil-L index. Like the other indices, it too starts out at a relatively high level, then exhibits a sharp reduction. However, unlike the other indices, it exhibits a pronounced recovery, retaining its original level. In other words, earnings mobility in France equalizes longer-term earnings as much now as it did thirty years ago. This runs counter to all of the other mobility concepts, each of which exhibits significantly less mobility now than before.

Another feature of the Fields-Theil-L index bears mention. As shown in the lower right panel of Figure 1, the index is always positive, save one value which is insignificantly less than zero. That the index is always positive during our analysis period means that mobility has an equalizing effect in France: that is, inequality in the base and final years taken together $I(x+y)$ is lower than inequality in the origin year, $I(x)$. Hence the ratio $I(x+y)/I(x)$ is below 1 and our index, 1 minus the ratio, is positive. France is unlike the United States in this regard; there, earnings mobility stopped equalizing longer-term incomes in the 1980s (Fields, 1999).

To what extent do the time paths of earnings mobility coincide with the time paths of cross-sectional earnings inequality? This question can be answered by comparing mobility patterns in Figure 1 with the inequality patterns shown in Figure 2. Five inequality measures are presented: the Gini coefficient, the standard deviation of log-earnings, and the 90:10, 50:10, and 90:50 ratios of log-earnings. These five measures all point to the same conclusion. Inequality strongly decreased in France between 1967 and 1999. Two periods must be contrasted though. The decline was extremely strong between 1967 and 1984. Starting in 1985, inequality pretty much stabilized. Taken together, Figures 1 and 2 show that earnings mobility leveled off about a decade earlier than earnings inequality did in France.

5. Comparing Mobility Across Groups: Further Results

In this section, we present evidence on the different mobility measures for different groups of the population. Three comparisons are made: by gender, by educational group, and by base year earnings decile. In the first two of these comparisons, the mobility measures are calculated within a group - for example, the positional movement of women within the women's earnings distribution is compared with the positional movement of men within the men's earnings distribution. For these two comparisons, we also present boostrapped 95 percent confidence interval. Of course, the indices by origin deciles cannot be computed <u>within</u> the origin deciles since workers' earnings may well move out of these origin deciles.

If we consider mobility differences between the sexes, we see that almost all changes in mobility across the period are parallel: when men's mobility is relatively high,

women's mobility is also; see Figure 3. What is remarkable, though, is that the six mobility concepts do not agree on which gender has more mobility. The rank-based measures – minus chi-square (a measure of time-independence) and per capita centile movement (a measure of positional movement) – are both significantly larger for women than for men. Conversely, the share movements (a relative mobility measure) are slightly larger for men than for women. Finally, the other three indices – all franc-based – essentially coincide for the two sexes.

Differences across education groups are particularly striking; see Figure 4.[3] The high education group stands out. When rank-based measures are used (per capita centile movement and minus chi-squared), these highly-educated workers are much less mobile than workers with less education. On the other hand, when mobility is measured in francs or "relative" francs, the highly–educated workers exhibit more movement than workers with lower education. These results are consistent with the large spread at the top of the wage distribution.

Finally, Figures 5a and 5b present our mobility indices by decile of origin, i.e., we compute the index between t and $t+2$ for all workers who, in origin year t were in that decile.[4] Figure 5a presents results for the five lower deciles whereas Figure 5b presents statistics for the five higher deciles. In Figure 5a, all indices display very different levels for the lowest (first) decile as compared with the next four deciles. Whereas time-independence is *lower* for workers in the first decile compared with those in the next four, the other aspects of mobility (positional movement, share movement, earnings flux, and directional earnings change in logs) are all *higher* for workers in the first decile compared with the next four. There is always more mobility for workers coming from the first decile measured in ranks or in Francs than for those just above in the wage distribution. The structure is completely different when one focuses on workers in the higher deciles (Figure 5b). Here the richest (tenth) decile stands out. Workers coming from the tenth decile are sometimes found to be *more* mobile (for share movement and earnings flux) and sometimes *less* mobile (time-independence, positional movement, and directional earnings change in logs).

In summary, in this section, we have made three sets of comparisons: by gender, by educational group, and by base year earnings decile.[5] For these comparisons, the

[3] We do not present results for those workers with no known diploma since they are remarkably similar to those shown for the low-education workers.

[4] Except for the Fields-Theil-L index for which such measures by initial decile has little meaning.

[5] Differences by birth cohort were also studied. In figures that are not reported here, we compare the time paths of the six mobility indices for twelve birth cohorts (1912-1916, 1917-1921, 1922-1926, 1927-1931,..., 1962-1966, and 1967-1971). What we find is that all indices display the same behavior: there is more mobility at the beginning and at the end of the employment cycle than in the middle, generating a U-shaped relation across time. The upward segment at the end is particularly sharp for the per capita share movement index. We find too that all indices converge to the same level of mobility as previous generations. Taken together, these results indicate that there is no shift of the level of

different mobility concepts *do not give the same ordinal ranking.* Women can have higher or lower mobility than men; the best-educated can have higher or lower mobility than the others; and the richest and the poorest can have higher or lower mobility than those in the middle. These results make very clear that the answer to the question of who has more mobility than another depends critically on the very concept of mobility used.

6. Analyzing the Mobility Patterns

6.1. A Statistical Framework

The next question is, what makes for higher mobility according to each of the six concepts? To answer this question, we divided our observations into sex-education group-birth cohort-year cells, indexed i. For each of the cells that had at least ten observations (so that deciles could be defined), we calculated six within-group mobility indices for each year, sex, education group, and birth cohort group (full interaction), resulting in 868 valid observations. Because of the small number of observations, instead of centile movements, we computed decile movements. Denote by m_{it}^k the k-th mobility measure in cell i in period t. The extent of mobility as measured by m_{it}^k can be related to: time-invariant characteristics of i such as gender, age, and education; time-varying characteristics of i such as age-, education-, or gender-specific trends; and finally to economy-wide characteristics at each date t such as the economy wide fraction of workers of various ages and educational attainments, GDP per-capita growth, the unemployment rate, growth in the consumer price index (CPI) (inflation), and growth of the minimum wage. All equations have been estimated by OLS with cell-specific fixed effects using the following equations:

$$m_{it}^k = \beta^k x_{it} + \lambda^k z_t + \alpha_i^k + \epsilon_{it}^k \tag{12}$$

where x_{it} denotes the time-varying characteristics of the cell, z_t denotes the time-varying characteristics of the economy, α_i^k denotes the cell-specific fixed effects, and ϵ_{it}^k denotes the statistical residual. In this table, the only covariates that can be presented are time-varying, because of the presence of fixed effects. Then, since we estimate equation (12) within cells, to recover the cell-specific effect, we calculate the effect for cell k as

$$\hat{\alpha}^k = \frac{1}{T} \sum (m_{it}^k - \widehat{\beta}^k x_{it} - \hat{\lambda}^k z_t) \tag{13}$$

and regress it on time-invariant characteristics of the cell (sex, education, and birth cohort), as shown in the following equation:

mobility across generations, but only intra-generational effects at entry and at exit. In this case, the different mobility concepts demonstrate essentially the same qualitative patterns.

$$\hat{\alpha}^k = \gamma^k w_i + v_i \tag{14}$$

We turn now to the results.

6.2. Estimates of the Mobility Equations

A regression analysis, presented in Table 3, shows the determinants of mobility at the aggregate level for each of our six indices. What stands out is the significantly negative relationship between the minimum wage level and most of these aggregate mobility indices. However, almost none of the other economic variables has a systematic impact on our six indices.

Our next concern is to look more deeply at other determinants of mobility. To do this, we take the cell ($n = 828$) as the unit of observation and regress each of the six measures of mobility on characteristics of the cell (age, education, gender), characteristics of the economy (GDP per capita growth rate, unemployment rate, minimum wage growth rate, inflation rate), and interaction variables (time trend, percentage of workers in a particular age-education cell).

Table 4 presents the results of estimating the six equations of type (12). Here is what we find. The regression for minus chi-square is shown in column (1). Its variation is only explained by the age of the individuals (they are more mobile when they are over age 50 or under age 30) and by the interaction between low-education and time. However, the economy-wide variables (employment composition – by age and education – and other macro-variables) do not affect the time-independence aspect of mobility. Turning now to per capita decile movement, which is an index of positional movement, the results are similar to those for minus chi-square. Column (2) shows that: per-capita decile movements are not affected by macro-economic conditions. However, they are strongly sensitive to age effects – workers in their 30s or 40s are less mobile - and to the interaction between high education and time. Column (3) presents the results for share movements. Surprisingly, no time-varying variable is found to have any impact on within-group mobility. Notice though that the fixed effects by themselves explain more than 60% of the variance in share movement. Results for the non-directional changes in logarithms (i.e., in absolute value) are presented in column (4). Here again, the age effects have a U shape; the mobility is lowest for those in their 40s. And, as before, macro-economic variables have no impact on mobility.[6]

It is customary for labor economists to analyze the logarithm of wages. Mobility results based on this (directional) measure stand in stark contrast to all others: nearly

[6] For all these regressions, the standard errors are not corrected for cluster-specific effects at the cell (age, education, sex) level (see Moulton, 1987). Their inclusion would just increase standard errors, and would not affect our conclusions since most variables have either a large effect or none.

all coefficients are significantly different from zero. Mobility is decreasing with age in the cell, with time (similarly for men and women), in particular for the highly educated. The percentage of workers who are young and middle-age in the economy (employment composition) increases log-wage mobility. Minimum wage increases have the same effect but GDP growth or inflation tend to decrease directional mobility. The large R-square of this regression may appear to be in contradiction with the following. Whereas personal characteristics, observed or unobserved, do a good job at explaining log-wages in individual-level regressions, the same characteristics, observed or unobserved, do much less well in first difference regressions of the same log-wage (for France, see Bayet and Colin, 1998, who show that the inclusion of person indicators or firm indicators does not contribute much to explaining the variance of wages when estimated in first difference; see also Abowd, Kramarz, and Margolis, 1999). Note indeed that our analysis is performed at the level of the cell. Hence, in comparison with the above person-level regressions, our analysis is more of a cross-sectional than "first-difference" nature. In addition, some of our regressors are generally not directly introduced at the person level.

Finally, the last column shows results for the Fields-Theil index. Apart from a general increasing trend, common to all cells, no other variable appears significant.

6.3. Explaining the Fixed Effects

Table 5 presents estimates of equation:

$$\hat{\alpha}^k = \gamma^k w_i + v_i$$

in which the fixed effect as estimated from the previous equation is regressed on all time-invariant characteristics of the cells, viz., gender, educational group, and birth cohort. Such regressions can be interpreted as showing the deep structure, i.e. after controlling for time-varying components, of our mobility indices. These effects are measured between cells whereas the previous results were computed within cells.

For the six regressions in Table 5, some of the results are quite similar for the various mobility concepts and some are quite different. Focusing first on the role of gender, we see that for all indices but one (the per capita directional change in logarithms), the male cells have more mobility ceteris paribus than the female cells. That is, men have more mobility within their distributions than women have within theirs.

By contrast, education has a much more varied effect on our six measures of mobility (the reference is the no-education group). For the chi-square as well as the Fields-Theil indices, the more educated are *less* mobile than those holding lower (or no) diplomas. Exactly the opposite is the case for share movement and directional and non-directional changes in log-francs; for these three measures, highly educated workers are *more* mobile than their less-educated counterparts. Finally, positional movements (decile movements)

show a U-shaped structure: middle-education workers are less mobile than the low-education workers but the high-education workers are much more mobile than low-education workers.

The effect of birth cohort is also quite diverse (the reference comprises all workers born after 1971). For three of our indices (chi-square movement, decile movement, and Fields-Theil), older cohorts are *less* mobile than younger ones. In stark contrast, directional movement (in logarithms) shows *more* movements for the older cohorts. Finally, the pattern is *flat or slightly U-shaped* for the last two indices (share movement and non-directional change in logs).

A trait common to all six regressions is the very high R-squared of the regressions presented in Table 5. And remember that, now, the regression does not include fixed effects any more. Hence, mobility as we measure it, appears to be structural more than cyclical. From such results, it seems that the chi-square index and the Fields-Theil measure have quite similar structures. Surprisingly, the directional change in logarithms measure is quite close to those two measures but moves in the opposite direction. Finally, the other three indices are difficult to compare based solely on these results.

7. Correlations Between Indices

To gain a better understanding of the potential relations between the various indices, we computed their correlations. First, we analyze the results at the aggregate level (31 points for each index, corresponding to the 31 pairs of years of our descriptive analysis). They are presented in Table 6. Consistent with the structure of the graphs in Figure 1, the correlations are very high ranging from 0.55 to 0.94.

Of course, such a result does not say anything about the co-variation of the indices at a more disaggregated level. Hence, we compute the correlation among indices using our 868 gender-education-birth cohort cells. These results are presented in Table 7. Recalling our previous regressions, presented in Table 4, we know that these correlations include time-varying characteristics. But, already, we see that there is much less resemblance between the various indices; these correlations range in absolute value from 0.02 to 0.87. Unfortunately, these numbers are difficult to interpret since they include the influence of economic shocks. One may notice that a group of highly correlated indices appears: it comprises the decile movement, the share movement, the directional and the non-directional change in logarithms measures. Notice also that the minus chi-square and the per-capita decile movement are highly correlated but that the former is not correlated to the three other indices that belong to the group just mentioned. In addition, the Fields-Theil index is never highly correlated with another index.

A way to eliminate the influence of the time-varying characteristics of the groups and of the macroeconomic variations in order to concentrate on the long-run factors is to examine the correlation of the indices using the estimates of the fixed effects calculated

from each of the equations (12). These results are presented in Table 8. They appear to be more clear-cut and easier to characterize than earlier ones. We may view the resulting correlations between these six indices as much closer to their underlying structure of the French economy. This structure is quite similar to the one that emerged from the fixed-effects regressions presented in Table 5. There are **two** groups of indices. The first one comprises the chi-square, the directional changes in logarithms, and the Fields-Theil index of redistribution. Interestingly, the directional change in logs is highly correlated to the other two but negatively. The second group of indices includes the decile movement, the share movement, and the non-directional change in logarithms measures. A brief examination of Table 8 shows the following. Take any couple of indices with the first element in the first group and the second element in the second group. Consider the correlations of these two indices with the remaining four. Then, we observe that at least one of the two indices has a correlation with the remaining four greater than 0.6.

These are very surprising results. In particular, the two rank-based indices – chi-square and decile movements – are positively correlated with each other. But, each of them can be more positively (or negatively) correlated with franc-based measures. For instance, the chi-square index, a rank-based measure, is much more correlated with the per-capita directional change in logs (negatively) and with the Fields-Theil index (positively), two franc-based measures. Hence, we can conclude that the chi-square is not only a ranks measure. In fact, the three measures belonging to the first group all show more mobility for the low-education workers than for the high-education ones.[7] On the other hand, the other three measures display more mobility for the better-educated than for the less educated workers. Among this group, the decile movement index exhibits more mobility for the low-education than for the middle-education workers, but, as mentioned just above, more mobility for the highly educated than for the low-education workers.

Therefore, summarizing mobility indices as rank-based indices or franc-based indices is important but it is far from the whole story.

8. Conclusions

In this paper, we have used administrative data from the French *Déclarations Annuelles de Salaires* and the *Echantillon Démographique Permanent* to gauge earnings mobility in France for various times and for various groups. Six different mobility concepts have been used. Our main conclusion is that the various measures differ qualitatively. Specifically:

[7] The directional change in logs has to reversed since it is negatively correlated to the two other indices of this group.

o We have analyzed six mobility concepts, using an index of each. Five of these six concepts show that mobility in France has fallen over time. The one exception is mobility as an equalizer of longer-term income, which is not appreciably lower now than it had been thirty years earlier. Also, mobility as an equalizer of longer-term income has always been positive in France (i.e., two-year incomes are more equally distributed than base-year income). France is unlike the United States in this respect, where mobility stopped equalizing longer-term incomes in the early 1980s.

o When earnings mobility was falling in France, earnings inequality was falling also. However, earnings mobility leveled off about a decade earlier than earnings inequality did.

o Comparing earnings mobility across groups, we find that the choice of a mobility concept and a corresponding index to measure it makes an important difference. Specifically, women have more earnings mobility than men for some mobility concepts, equal mobility for others, and less mobility for others. The same is true by educational group: The best-educated workers have more earnings mobility than others for some mobility concepts, equal mobility for other mobility concepts, and less mobility for still others. It is also true when comparing workers who started in different base year deciles. For one mobility concept, those who started in the highest and lowest earnings deciles exhibit lower earnings mobility than those who started in the middle earnings deciles. For two other mobility concepts, those who started in the highest and lowest earnings deciles exhibit higher earnings mobility than those who started in the middle earnings deciles. And for two other mobility concepts, those who started in the highest earnings decile are at the opposite end of the mobility scale from those who started in the lowest earnings decile.

o A statistical framework was posited and used to analyze the mobility patterns. The strongest results are found for per capita directional change in log-francs. For this variable, virtually all of the personal characteristics and economy-wide characteristics are statistically significant. Weak results are found for all of the other mobility concepts. Fixed effects play an important role.

o Empirically, in France, the six indices coalesce into two groups. The first group consists of chi-square, directional change in log-francs, and the Fields-Theil index of redistribution. The second group includes decile movement, share movement, and non-directional change in log-francs.

o No single index summarizes the mobility process by itself. At least two indices are necessary: one from the first group and one from the second group. But, the composition of these two groups are not rank-based versus franc-based. Two franc-based indices or two rank-based indices may well do better when describing mobility than a "mixed" couple.

Overall, this research shows that the six different mobility concepts yield quite different results. The great bulk of the earnings mobility literature in France, as in most

other countries, is position-based. In view of what we have found, researchers should be careful to specify which mobility concept or concepts they are most interested in and choose their measures carefully.

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APPENDIX A: THE USE OF THE BOOTSTRAP METHOD

In this appendix we explain the use of the bootstrap method in the computation of the standard error and confidence intervals for the estimates of the mobility measures. The method was introduced in Andrews and Buchinsky (2000). We summarize it here for completeness.

Standard Error Results

The observed data are a sample of size n: $\mathbf{X} = (X_1, ..., X_n)'$, where X_i $(i = 1, ..., n)$ are $T \times k$ matrices containing the data on k variables for T time periods. Denote the true measure of mobility by θ_0, and let $\widehat{\theta} = \widehat{\theta}(\mathbf{X})$ be the estimator for θ_0 based on the sample $\mathbf{X}$. Denote the standard error of $\widehat{\theta}$ by se, that is,

$$se = \left(E(\widehat{\theta}(\mathbf{X}) - E\widehat{\theta}(\mathbf{X}))^2\right)^{1/2}. \tag{15}$$

Let $\mathbf{X}^* = (X_1^*, ..., X_n^*)'$ be an iid sample of size n based on the original sample $\mathbf{X}$. That is, we draw n individuals from the original sample with replacement. Then the "ideal" bootstrap standard error estimator of se is

$$\widehat{se}_\infty = \left(E^*(\widehat{\theta}(\mathbf{X}^*) - E^*\widehat{\theta}(\mathbf{X}^*))^2\right)^{1/2}, \tag{16}$$

where E^* denotes expectation with respect to the randomness in the bootstrap sample $\mathbf{X}^*$ conditional on the observed data $\mathbf{X}$.

Consider B iid bootstrap samples $\{\mathbf{X}_b^* : b = 1, ..., B\}$, each with the same distribution as $\mathbf{X}^*$, with the corresponding B bootstrap estimates of θ_0 given by $\widehat{\theta}_b^* = \widehat{\theta}(\mathbf{X}_b^*)$ for $b = 1, ..., B$. The bootstrap standard error estimator for B bootstrap repetitions is

$$\widehat{se}_B = \left(\frac{1}{B-1}\Sigma_{b=1}^B \left(\widehat{\theta}_b^* - \frac{1}{B}\Sigma_{c=1}^B \widehat{\theta}_c^*\right)^2\right)^{1/2}. \tag{17}$$

The problem is how to use enough bootstrap repetitions, B, so that $\widehat{se}_B$ and $\widehat{se}_\infty$ be close enough with high probablity. This is what we address below (for more detailed consideration see Andrews and Buchinsky (2000)).

Let μ and γ_2 denote the *mean* and the *coefficient of excess kurtosis* of the bootstrap estimator $\widehat{\theta}_b^*$, that is,

$$\begin{aligned} \mu &= E^*\widehat{\theta}(\mathbf{X}^*), \quad \text{and} \\ \gamma_2 &= \frac{E^*(\widehat{\theta}(\mathbf{X}^*) - \mu)^4}{\widehat{se}_\infty^4} - 3. \end{aligned} \tag{18}$$

Consistent estimates of μ and γ_2 are given by

$$\begin{aligned} \widehat{\mu}_B &= \frac{1}{B}\Sigma_{b=1}^{B}\widehat{\theta}_b^* \text{ and} \\ \widehat{\gamma}_{2B} &= \frac{\frac{1}{B-1}\Sigma_{b=1}^{B}(\widehat{\theta}_b^* - \widehat{\mu}_B)^4}{\widehat{se}_B^4} - 3. \end{aligned} \tag{19}$$

Let $\chi^2_{1-\tau}$ denote the $(1-\tau)$-th quantile of a chi-squared distribution with one degree of freedom for $\tau \in (0,1)$.

In the following we determine the optimal B, that is $B = B(pdb, \tau)$ such that

$$P^*\left(100\frac{|\widehat{se}_B - \widehat{se}_\infty|}{\widehat{se}_\infty} \leq pdb\right) = 1 - \tau, \tag{20}$$

where pdb denotes the bound on the percentage deviation of $\widehat{se}_B$ from $\widehat{se}_\infty$. It follows that

$$B \doteq 2,500\chi^2_{1-\tau}(2+\gamma_2)/pdb^2. \tag{21}$$

The following three-step method for determining B achieves the desired accuracy of $\widehat{se}_B$ for estimating $\widehat{se}_\infty$, specified by the (pdb, τ) combination:

Step 1. Set $\gamma_2 = 0$ and use (21) to specify a preliminary value of B, denoted B_0, that is,

$$B_0 = \text{int}(5,000\chi^2_{1-\tau}/pdb^2), \tag{22}$$

where int(a) denotes the smallest integer greater than or equal to a.

Step 2. Simulate B_0 bootstrap estimates $\{\widehat{\theta}_b^* : b = 1, ..., B_0\}$ and compute $\widehat{\gamma}_{2B_0}$ as defined in (19) with B replaced by B_0.

Step 3. Take the desired number of bootstrap repetitions, B^*, to equal $B^* = \max\{B_1, B_0\}$, where

$$B_1 = \text{int}(2,500\chi^2_{1-\tau}(2+\widehat{\gamma}_{2B_0})/pdb^2). \tag{23}$$

The justification of the above method is that as $pdb \to 0$, we have $B_1 \to \infty$ and

$$P^*\left(100\frac{|\widehat{se}_{B_1} - \widehat{se}_\infty|}{\widehat{se}_\infty} \leq pdb\right) \to 1 - \tau \tag{24}$$

provided $\gamma_2 > -2$.

A better method to use is a method that corrects for possible bias in the parameter estimate $\widehat{\gamma}_{2B_0}$ for γ_2. This bias-corrected method requires minimal additional computation.

A Bootstrap Bias-Corrected Estimator of γ_2

Consider the iid sample of B_0 bootstrap estimates of θ_0 in Step 2 of the three-step method described above, that is $\mathbf{\Theta}^* = (\widehat{\theta}_1^*, ..., \widehat{\theta}_{B_0}^*)$. By definition, γ_2 is the coefficient of excess kurtosis of the distribution of $\widehat{\theta}_b^*$ for any $b = 1, ..., B_0$. Therefore we can we think of $(\widehat{\theta}_1^*, ..., \widehat{\theta}_{B_0}^*)$ as being an original sample and $\widehat{\gamma}_{2B_0}$ as being an estimator based on this sample that we want to bootstrap bias correct.

Let the bootstrap sample $\mathbf{\Theta}^{**} = (\widehat{\theta}_1^{**}, ..., \widehat{\theta}_{B_0}^{**})$ be a random sample of size B_0 drawn from $\mathbf{\Theta}^*$. Let $\widehat{\gamma}_2(\mathbf{\Theta}^{**})$ denote the estimate $\widehat{\gamma}_{2B_0}$ of γ_2 computed using the bootstrap sample $\mathbf{\Theta}^{**}$, rather than the original sample $\mathbf{\Theta}^*$. That is,

$$\widehat{\gamma}_2(\mathbf{\Theta}^{**}) = \frac{\frac{1}{B_0-1}\sum_{b=1}^{B_0}\left(\widehat{\theta}_b^{**} - \frac{1}{B_0}\sum_{j=1}^{B_0}\widehat{\theta}_j^{**}\right)^4}{\left(\frac{1}{B_0-1}\sum_{b=1}^{B_0}\left(\widehat{\theta}_b^{**} - \frac{1}{B_0}\sum_{j=1}^{B_0}\widehat{\theta}_j^{**}\right)^2\right)^2} - 3. \tag{25}$$

Note also that $\widehat{\gamma}_{2B_0} = \widehat{\gamma}_2(\mathbf{\Theta}^*)$.

The "ideal" bootstrap estimate of the bias of $\widehat{\gamma}_{2B_0}$ for estimating γ_2 is given then by

$$E^{**}\widehat{\gamma}_2(\mathbf{\Theta}^{**}) - \widehat{\gamma}_{2B_0}, \tag{26}$$

where E^{**} denotes expectation with respect to the randomness in $\mathbf{\Theta}^{**}$. Consequently, the "ideal" bootstrap bias-corrected estimate $\widehat{\gamma}_{2B_0\infty}$ of γ_2 is

$$\widehat{\gamma}_{2B_0\infty} = \widehat{\gamma}_{2B_0} - (E^{**}\widehat{\gamma}_2(\mathbf{\Theta}^{**}) - \widehat{\gamma}_{2B_0}) = 2\widehat{\gamma}_{2B_0} - E^{**}\widehat{\gamma}_2(\mathbf{\Theta}^{**}). \tag{27}$$

Since analytic calculation of the ideal bootstrap bias-corrected estimate of γ_2 is intractable, we can approximate it using bootstrap simulations. Consider R independent bootstrap samples $\{\mathbf{\Theta}_r^{**} : r = 1, ..., R\}$, where each bootstrap sample $\mathbf{\Theta}_r^{**} = (\widehat{\theta}_{1r}^{**}, ..., \widehat{\theta}_{B_0r}^{**})$ is a random sample of size B_0 drawn from $\mathbf{\Theta}^*$. The corresponding R bootstrap estimates of γ_2 are $\widehat{\gamma}_2(\mathbf{\Theta}_r^{**})$ for $r = 1, ..., R$. The bootstrap bias-corrected estimator $\widehat{\gamma}_{2B_0R}$ of γ_2 for R bootstrap repetitions is

$$\widehat{\gamma}_{2B_0R} = 2\widehat{\gamma}_{2B_0} - \frac{1}{R}\sum_{r=1}^{R}\widehat{\gamma}_2(\mathbf{\Theta}_r^{**}). \tag{28}$$

Now, the three-step method can be altered adding a step between Steps 2 and 3 in which $\widehat{\gamma}_{2B_0R}$ is calculated (and replaces $\widehat{\gamma}_{2B_0}$ in Step 3). The added step is:

Step 2(b). Simulate R bootstrap samples $\{\mathbf{\Theta}_r^{**} : r = 1, ..., R\}$, compute R bootstrap estimates $\{\widehat{\gamma}_2(\mathbf{\Theta}_r^{**}) : r = 1, ..., R\}$ from these samples using (25), and compute $\widehat{\gamma}_{2B_0R}$ from these bootstrap estimates and $\widehat{\gamma}_{2B_0}$ using (28).

Confidence Interval Results

As in the previous section, $\mathbf{X}$ denotes the observed data and $\widehat{\theta} = \widehat{\theta}(\mathbf{X})$ is an estimator of the unknown mobility measure θ_0. We wish to construct a symmetric confidence interval for θ_0 of (approximate) confidence level $100(1-\alpha)\%$ for some $0 < \alpha < 1$. In all case considered in this paper the estimators for the mobility measures have asymptotic normal distribution as $n \to \infty$.

Let $\widehat{\sigma} = \widehat{\sigma}(\mathbf{X})$ denote a consistent estimator of the asymptotic standard error of $n^{\kappa}(\widehat{\theta} - \theta_0)$. Let

$$T = n^{\kappa}(\widehat{\theta} - \theta_0)/\widehat{\sigma} \tag{29}$$

denote the t statistic for testing whether $\theta = \theta_0$. The t statistic has an asymptotic standard normal distribution when the true parameter is θ_0.

The "theoretical" symmetric percentile t confidence interval of confidence level $100(1-\alpha)\%$ is

$$J_{SY} = [\widehat{\theta} - n^{-\kappa}\widehat{\sigma}k_{\alpha}, \widehat{\theta} + n^{-\kappa}\widehat{\sigma}k_{\alpha}], \tag{30}$$

where k_{α} is the solution to

$$P(|T| \leq k_{\alpha}) = 1 - \alpha. \tag{31}$$

Note that by the definition of k_{α}, J_{SY} has exact confidence level $100(1-\alpha)\%$.

Define a bootstrap sample $\mathbf{X}^* = (X_1^*, ..., X_n^*)'$ and a bootstrap estimator $\widehat{\theta}^* = \widehat{\theta}(\mathbf{X}^*)$ as in the previous section. Let $\widehat{\sigma}^* = \widehat{\sigma}(\mathbf{X}^*)$ denote the asymptotic standard error estimator based on the bootstrap sample $\mathbf{X}^*$. Let $T^* = n^{\kappa}(\widehat{\theta}^* - \widehat{\theta})/\widehat{\sigma}^*$ denote the bootstrap t statistic based on $\mathbf{X}^*$. Let $\widehat{k}_{\alpha,\infty}$ denote the *ideal bootstrap estimate* of k_{α}, where, for preciseness, we define $\widehat{k}_{\alpha,\infty} = \inf\{k : P^*(|T^*| \leq k) \geq 1 - \alpha\}$, where $P^*(\cdot)$ denotes probability with respect to the bootstrap sample $\mathbf{X}^*$ conditional on the original sample $\mathbf{X}$.

The ideal bootstrap symmetric percentile t confidence interval of approximate confidence level $100(1-\alpha)\%$ is

$$\widehat{J}_{SY,\infty} = [\widehat{\theta} - n^{-\kappa}\widehat{\sigma}\widehat{k}_{\alpha,\infty}, \widehat{\theta} + n^{-\kappa}\widehat{\sigma}\widehat{k}_{\alpha,\infty}]. \tag{32}$$

Here we approximate $\widehat{k}_{\alpha,\infty}$ using bootstrap simulations.

As above, consider B iid bootstrap samples $\{\mathbf{X}_b^* : b = 1, ..., B\}$, each with the same distribution as $\mathbf{X}^*$, and the corresponding bootstrap statistics $\widehat{\theta}_b^*$ $(= \widehat{\theta}(\mathbf{X}_b^*))$, $\widehat{\sigma}_b^*$ $(= \widehat{\sigma}(\mathbf{X}_b^*))$, and $T_b^* = n^{\kappa}(\widehat{\theta}_b^* - \widehat{\theta})/\widehat{\sigma}_b^*$ for $b = 1, ..., B$. Let $\{|T^*|_{B,b} : b = 1, ..., B\}$ denote the ordered sample of the absolute values of T_b^*.

We choose B to be an positive integer satisfying $\nu/(B+1) = 1-\alpha$ for some positive integer ν. This implies that α is rational. For such B the bootstrap estimate of k_{α} is defined to be

$$\widehat{k}_{\alpha,B} = |T^*|_{B,\nu}. \tag{33}$$

That is, $\widehat{k}_{\alpha,B}$ is the ν-th order statistic of $\{|T_b^*| : b = 1, ..., B\}$. Furthermore, the bootstrap symmetric percentile t confidence interval of approximate confidence level $100(1-\alpha)\%$ based on B bootstrap repetitions is

$$\widehat{J}_{SY,B} = [\widehat{\theta} - n^{-\kappa}\widehat{\sigma}\widehat{k}_{\alpha,B}, \widehat{\theta} + n^{-\kappa}\widehat{\sigma}\widehat{k}_{\alpha,B}]. \tag{34}$$

Note that B can be chosen as in the previous paragraph only if α is rational. We therefor choose

$$\alpha = \alpha_1/\alpha_2 \tag{35}$$

for some positive integers α_1 and α_2 (with no common integer divisors). It follows then that

$$B = \alpha_2 a - 1 \quad \text{and } \nu = (\alpha_2 - \alpha_1)a \tag{36}$$

for some positive integer a.

Denote the length of a confidence interval J by $L(J)$. We have

$$L(\widehat{J}_{SY,B}) = 2n^{-\kappa}\widehat{\sigma}\widehat{k}_{\alpha,B} \quad \text{and } L(\widehat{J}_{SY,\infty}) = 2n^{-\kappa}\widehat{\sigma}\widehat{k}_{\alpha,\infty}. \tag{37}$$

We measure the closeness of $\widehat{J}_{SY,B}$ to $\widehat{J}_{SY,\infty}$ by comparing the lengths of the two intervals. The percentage deviation of the length of $\widehat{J}_{SY,B}$ to the length of $\widehat{J}_{SY,\infty}$ is

$$100\frac{|L(\widehat{J}_{SY,B}) - L(\widehat{J}_{SY,\infty})|}{L(\widehat{J}_{SY,\infty})} = 100\frac{|\widehat{k}_{\alpha,B} - \widehat{k}_{\alpha,\infty}|}{\widehat{k}_{\alpha,\infty}}. \tag{38}$$

Using the notation of the previous section, we want to determine $B = B(pdb, \tau)$ such that

$$P^*\left(100\frac{|\widehat{k}_{\alpha,B} - \widehat{k}_{\alpha,\infty}|}{\widehat{k}_{\alpha,\infty}} \leq pdb\right) = 1 - \tau. \tag{39}$$

That is, we want to specify a method of determining B to obtain a desired level of accuracy pdb with probability (approximately) equal to $1 - \tau$.

The following three-step method is designed to do so. The method relies on an estimator of the reciprocal of a density function at a point, which appears in the asymptotic distribution of the sample quantile $\widehat{k}_{\alpha,B}$. For this, we use Siddiqui's (1960) estimator with the optimal plug-in estimator of the bandwidth parameter, suggested by Hall and Sheather (1988), that is chosen to maximize the higher order asymptotic coverage probability of the resultant confidence interval.

The three-step method is defined as follows:

Step 1. Compute a preliminary number of bootstrap repetitions B_0 via

$$\begin{aligned} B_0 &= \alpha_2 a_0 - 1, \text{ where} \\ a_0 &= \text{int}\left(\frac{2,500\alpha(1-\alpha)\chi^2_{1-\tau}}{z^2_{1-\alpha/2}\phi^2(z_{1-\alpha/2})pdb^2\alpha_2}\right) \text{ and } \alpha = \alpha_1/\alpha_2. \end{aligned} \tag{40}$$

Step 2. Simulate B_0 bootstrap t statistics $\{T_b^* : b = 1, ..., B_0\}$; order the absolute values of the bootstrap t statistics, which are denoted $\{|T^*|_{B_0,b} : b = 1, ..., B_0\}$; and calculate $\nu_0 = (\alpha_2 - \alpha_1)a_0$, $\widehat{m} = \text{int}(c_\alpha B_0^{2/3})$, $\widehat{k}_{\alpha,B_0} = |T^*|_{B_0,\nu_0}$, $|T^*|_{B_0,\nu_0-\widehat{m}}$, and $|T^*|_{B_0,\nu_0+\widehat{m}}$, where

$$c_\alpha = \left(\frac{6z_{1-\alpha/2}^2 \phi^2(z_{1-\alpha/2})}{2z_{1-\alpha/2}^2 + 1} \right)^{1/3}. \tag{41}$$

Step 3. Take the desired number of bootstrap repetitions, B^*, to equal $B^* = \max\{B_0, B_1\}$, where

$$\begin{aligned} B_1 &= \alpha_2 a_1 - 1 \text{ and} \\ a_1 &= \text{int}\left(\frac{10,000\alpha(1-\alpha)\chi_{1-\tau}^2}{\widehat{k}_{\alpha,B_0}^2 pdb^2\alpha_2} \left(\frac{B_0}{2\widehat{m}}\right)^2 \left(|T^*|_{B_0,\nu_0+\widehat{m}} - |T^*|_{B_0,\nu_0-\widehat{m}}\right)^2 \right). \end{aligned} \tag{42}$$

Note that $z_{1-\alpha/2}$ denotes the $(1-\alpha/2)$-th quantile of a standard normal distribution, $\phi(\cdot)$ denotes the standard normal density function, and $\chi_{1-\tau}^2$ denotes the $(1-\tau)$-th quantile of a chi-square distribution with one degree of freedom.

Having determined B^*, one simulates $B^* - B_0$ (≥ 0) additional bootstrap t statistics $\{T_b^* : b = B_0 + 1, ..., B^*\}$ and orders the absolute values of the B^* bootstrap t statistics, which are denoted $\{|T^*|_{B^*,b} : b = 1, ..., B^*\}$. The desired cutoff value, ν^*, and the desired critical point, $\widehat{k}_{\alpha,B^*}$, are then given by

$$\begin{aligned} \nu^* &= \max\{\nu_0, \nu_1\},\ \nu_1 = (\alpha_2 - \alpha_1)a_1, \text{ and} \\ \widehat{k}_{\alpha,B^*} &= |T^*|_{B^*,\nu^*}. \end{aligned} \tag{43}$$

The resulting bootstrap confidence interval, based on B^* bootstrap repetitions, is equal to

$$\widehat{J}_{SY,B^*} = [\widehat{\theta} - n^{-\kappa}\widehat{\sigma}\widehat{k}_{\alpha,B^*}, \widehat{\theta} + n^{-\kappa}\widehat{\sigma}\widehat{k}_{\alpha,B^*}]. \tag{44}$$

Appendix Table B.1.

Concept	Measure of That Concept
Time-dependence	Minus chi-squared
Positional-movement	Per-capita centile movement (absolute value)
Share-movement	Per-capita change in earnings share
Earnings flux	Per-capita change in francs (absolute value)
Directional earnings change	Per-capita change in log-francs
Equalization of longer-term incomes	Fields index, using the Theil coefficient as the measure of inequality

Figure 1 : Evolution of Wage Mobility, 1967–1999 (with 95 % confidence intervals)

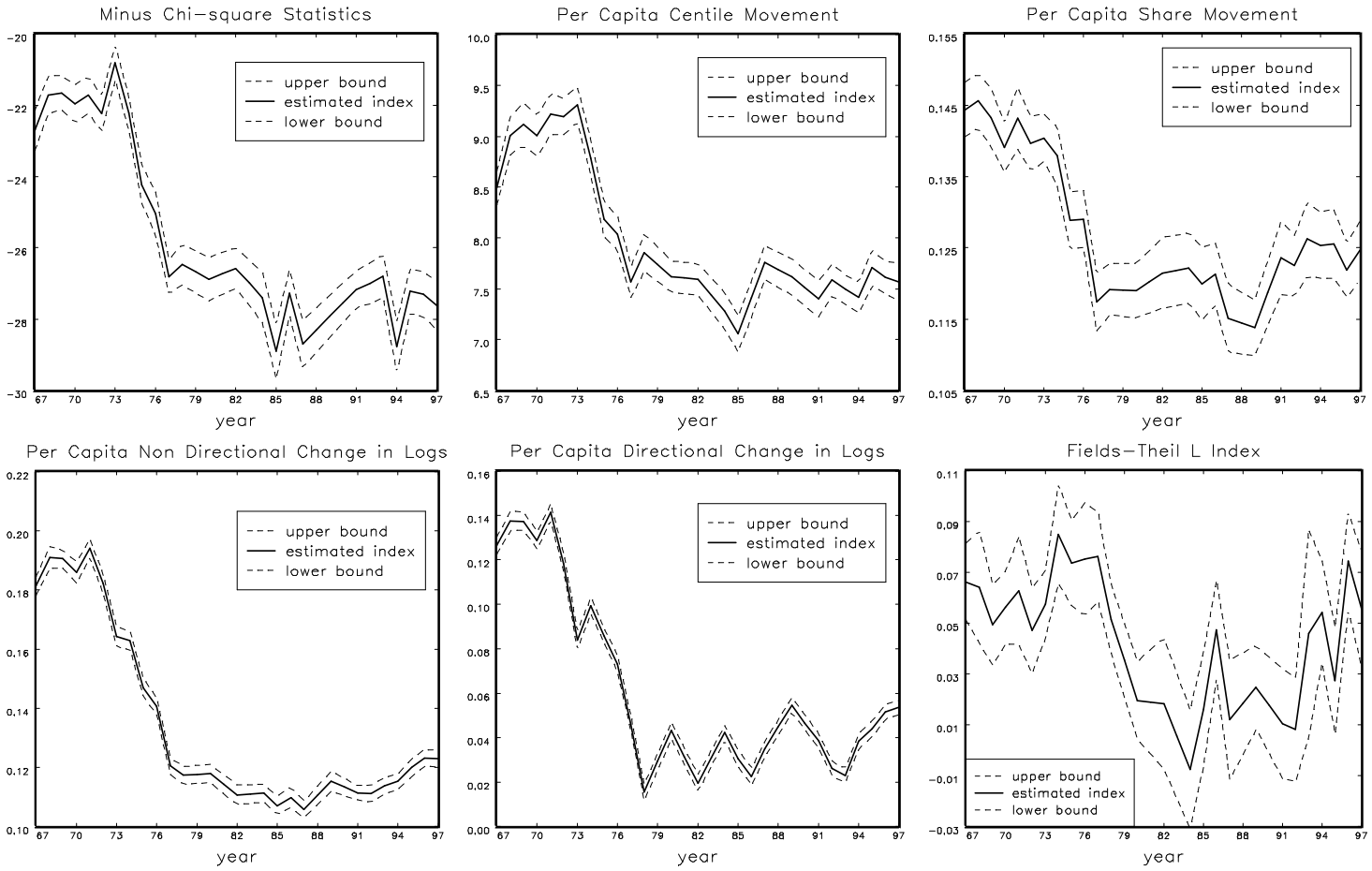

Figure 2 : Summary Measures of Wage Inequalities, France, 1967–1995

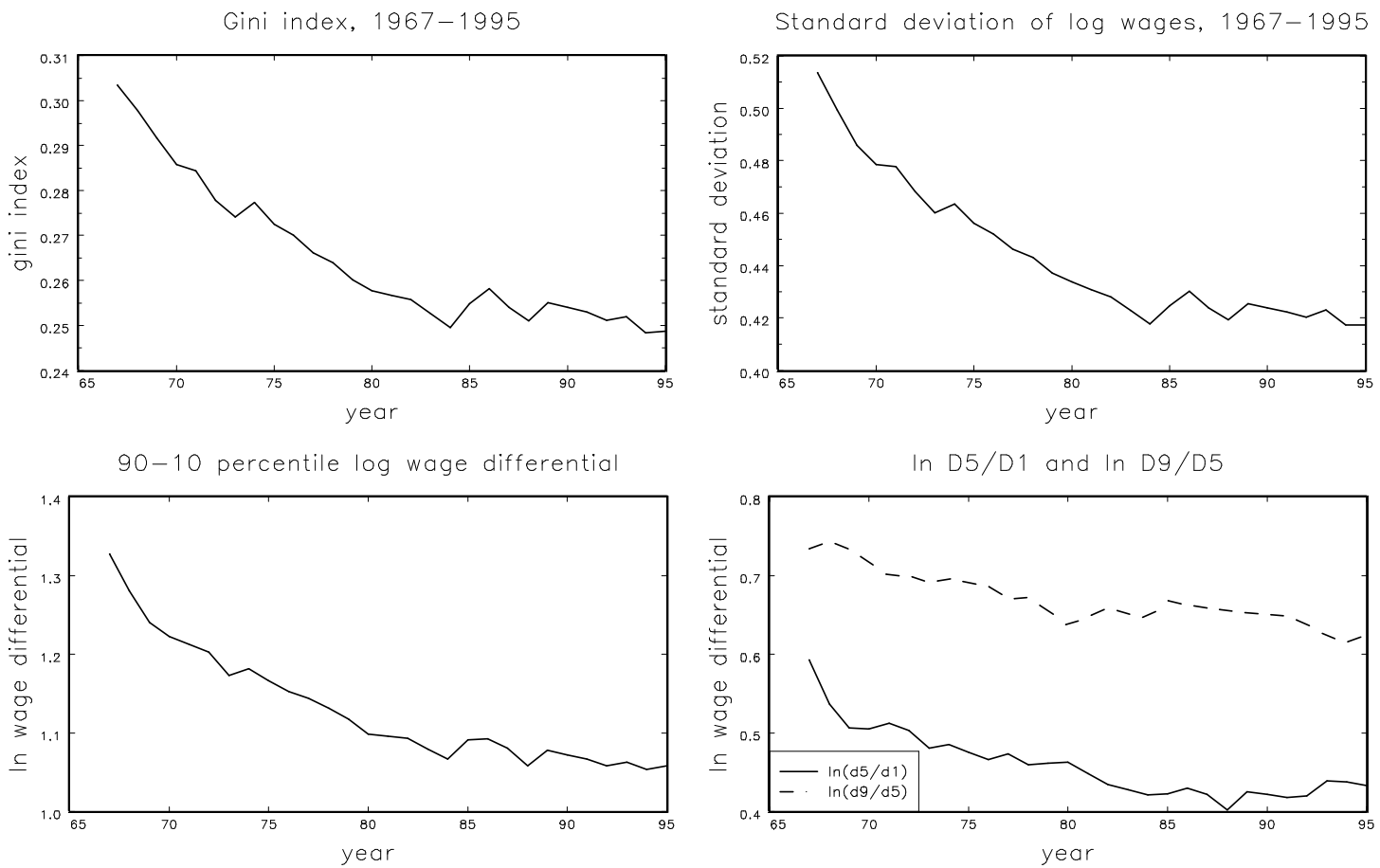

Figure 3. France: Evolution of Wage Mobility, 1967–1999, by Gender
(with 95 percent confidence intervals)

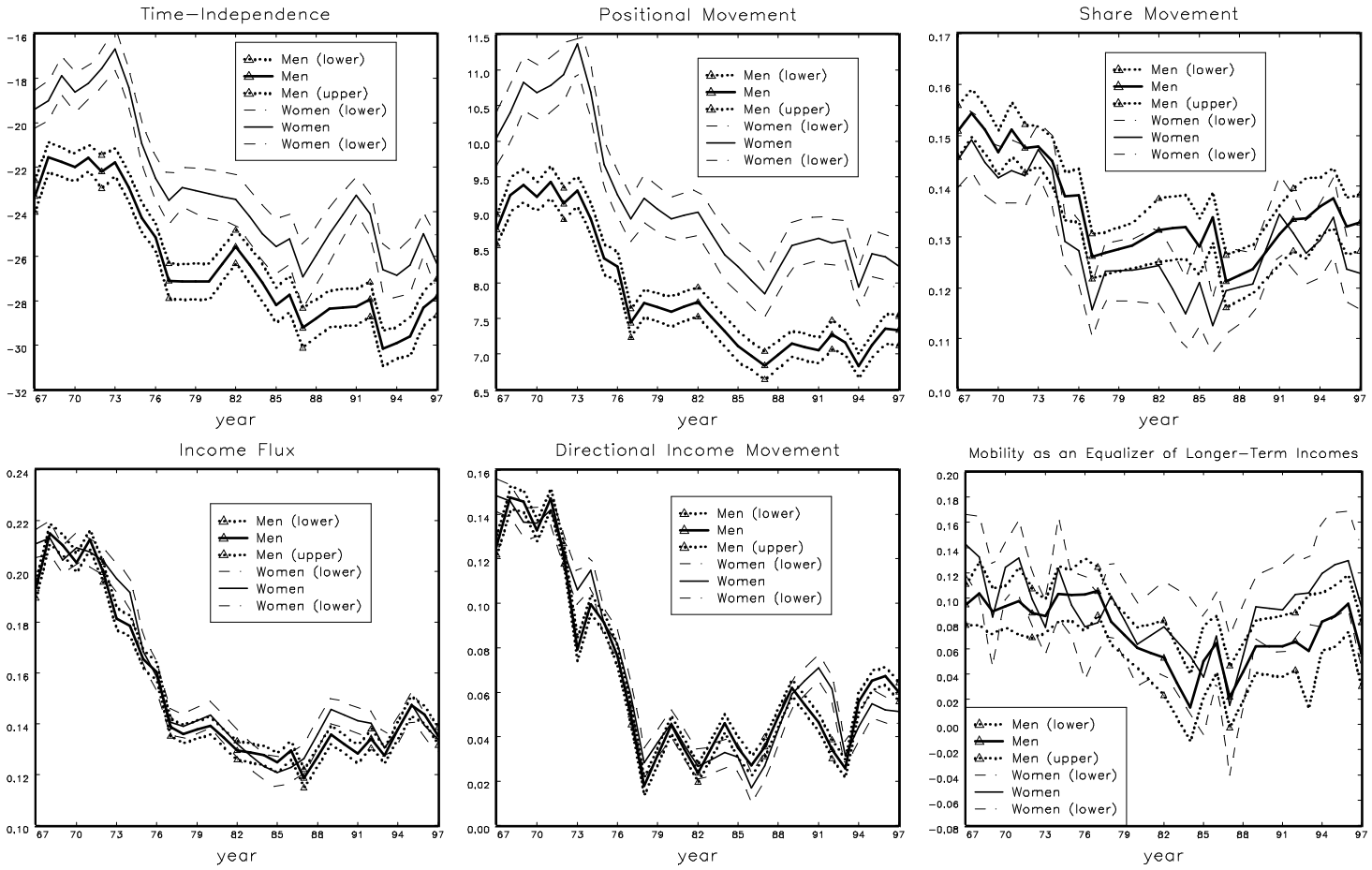

Figure 4: Wage Mobility, 1967–1999, by Education (with conf. int.)

(low: primary or junior high sch.; medium: technical sch.; high: secondary diploma and beyond)

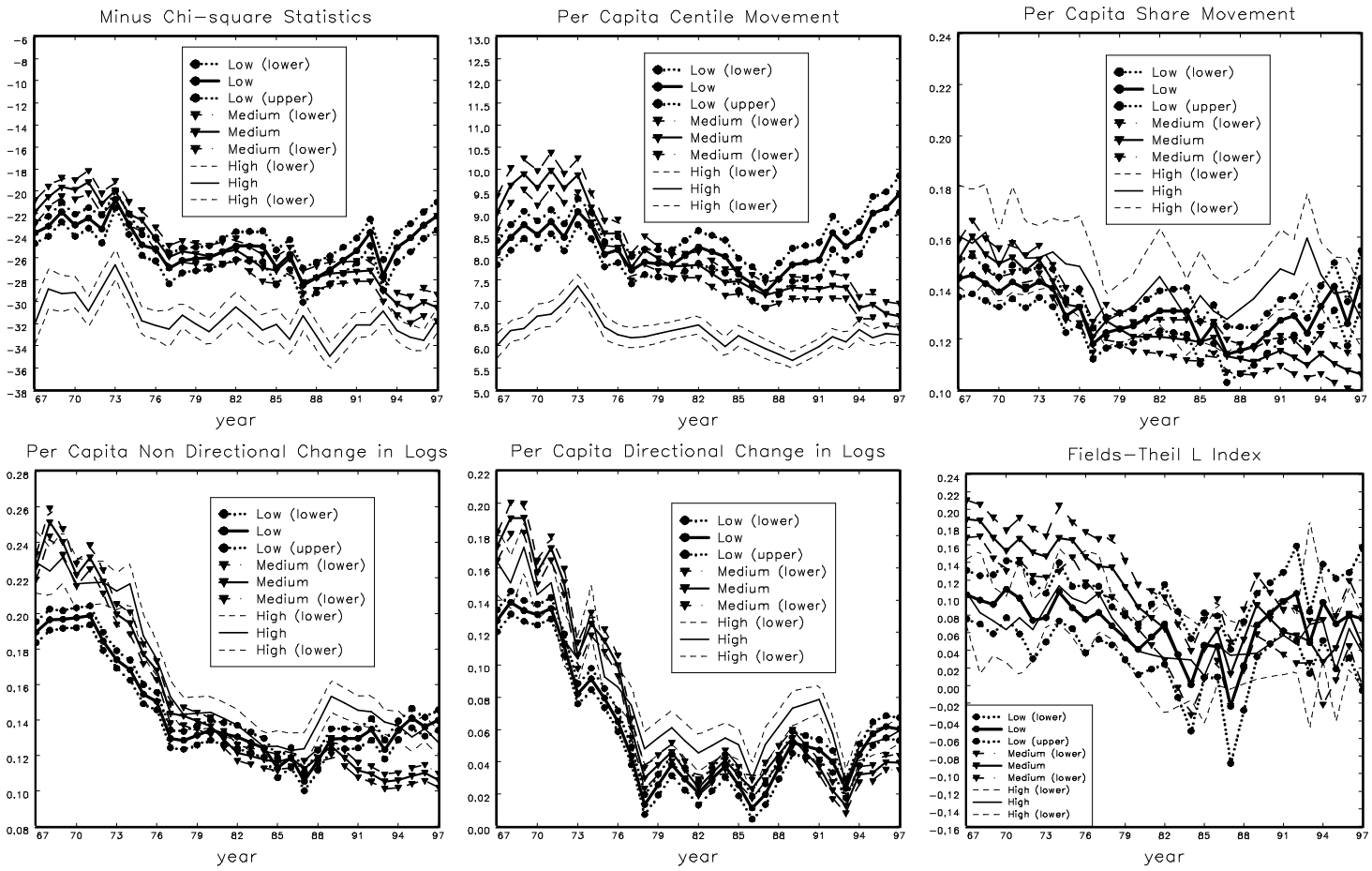

Figure 5a : Evolution of Wage Mobility, 1967–1999, by Decile in Origin Year

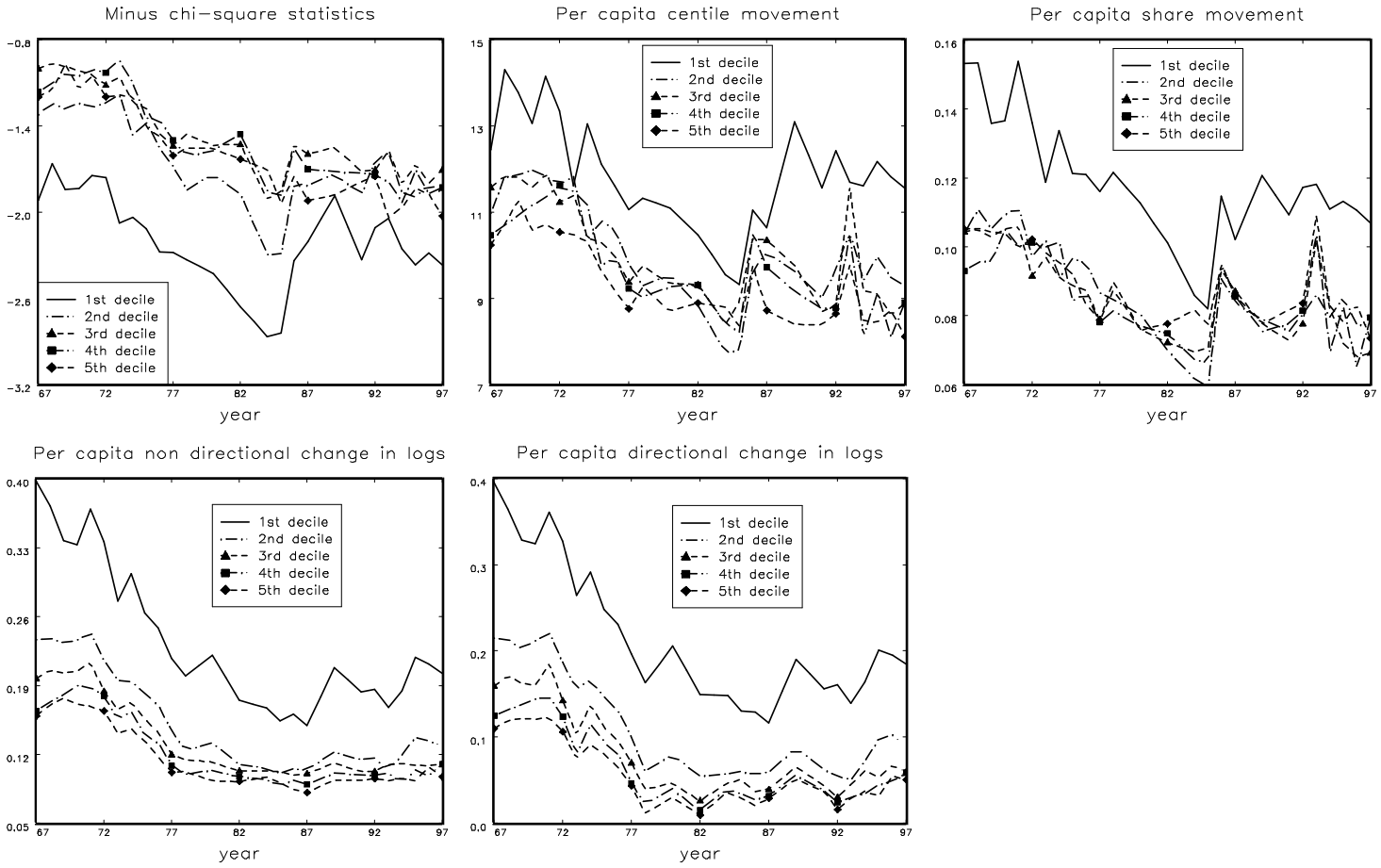

Figure 5b : Evolution of Wage Mobility, 1967–1997, by Decile in Origin Year

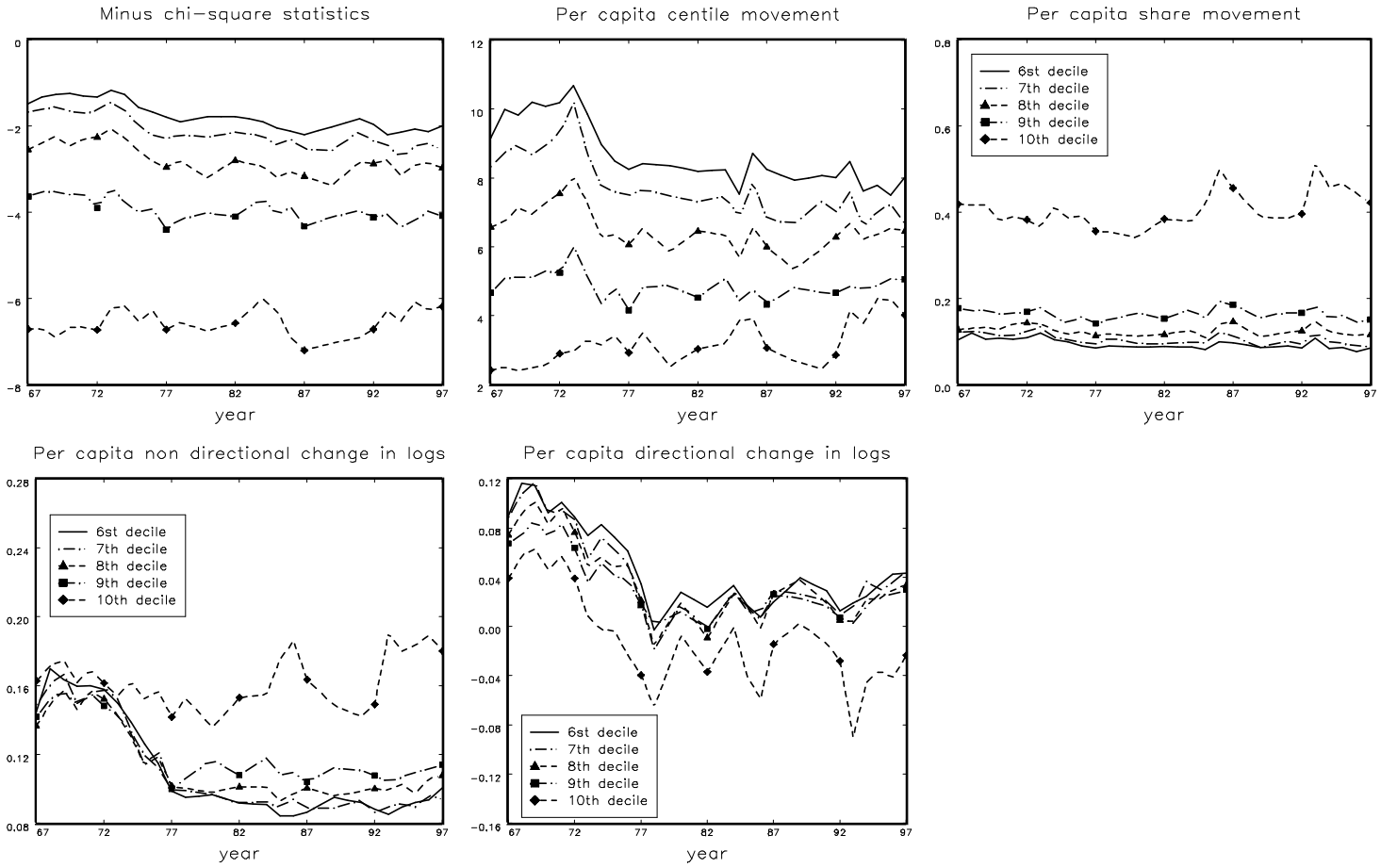

Table 1: Mobility Indices, 1997-1999

Group	Mean change in ranks, absolute values (deciles in the total population)	Mean change in francs, algebraic values	Mean change in francs, absolute values
Entire population	0.7448	1390.26	3488.70
By gender			
Male	0.7243	1554.57	3830.70
Female	0.7982	1098.51	2983.69
By educational group			
Low	0.9193	1474.44	3691.47
Medium	0.6487	1062.55	3021.63
High	0.6127	2278.59	5330.49
By decile in base year			
Lowest	1.1040	2809.62	3019.91
Second	0.9116	1612.18	2166.78
Fifth	0.7972	1267.89	2096.47
Ninth	0.5005	1788.30	4056.41
Tenth	0.3606	-130.55	10803.24

All the Statistics are computed within-group, except for computations by deciles. Hence, the distribution of reference is the group's. Sources: DADS-EDP

Table 2: Mobility Indices, 1967-1969

Group	Mean change in ranks, absolute values (deciles in the total population)	Mean change in francs, algebraic values	Mean change in francs, absolute values
Entire population	0.8395	1795.47	2757.26
By gender			
Male	0.8543	1904.93	3059.45
Female	0.9791	1523.33	2161.27
By educational group			
Low	0.7919	1695.46	2613.36
Medium	0.8762	2172.82	2998.74
High	0.5723	4154.65	6382.97
By decile in base year			
Lowest	1.1755	2832.91	2845.00
Second	1.0734	1899.14	2045.29
	1.0266	1516.35	1990.38
	0.4770	1915.45	3188.98
Etc.	0.2204	2466.89	6969.42

All the Statistics are computed within-group, except for computations by deciles. Hence, the distribution of reference is the group's. Sources: DADS-EDP

Table 3
Regression Analysis for Mobility Indices,

Levels	Minus Chi-Square	Centile Movement	Share Movement	Directional Change in Logs	Fields-Theil Index
Intercept	-20.14***	7.167***	0.153***	0.299	0.2142*
	(4.8570)	(1.8860)	(0.0222)	(0.0777)	(0.1097)
GDP per	48.835	48.586*	0.3321	-0.3999	-1.5827
capita	(63.7600)	(24.7620)	(0.2911)	(1.0206)	(1.4404)
Unemploy-	-0.6187*	0.0106	0.0001	-0.0065	-0.0012
ment rate	(0.3095)	(0.1202)	(0.0014)	(0.0050)	(0.0070)
Minimum	-0.5912*	-0.1241	-0.0049**	-0.025***	-0.0102
Wage	(0.2910)	(0.1130)	(0.0013)	(0.0047)	(0.0066)
CPI	1.0909*	0.2417	0.0039	0.0198*	-0.008
	(0.5886)	(0.2286)	(0.0027)	(0.0094)	(0.0133)
R^2	0.866	0.713	0.814	0.864	0.326

Source : DADS-EDP., 1967-1999, 31 observations
Notes : Significance levels of the estimates are 5% (*). 1% (**), 0.1% (***).
Standard errors between parentheses.

Table 4: Fixed Effect Regressions of the Mobility Indices

Mobility Indices:	Minus Chi-Square	Per Capita Decile Movement	Per Capita Share Movement	Per Cap.non Directional Change in Logs	Per Capita Directional Change in Logs	Fields-Theil Index
	Coefficient (Std. Err.)	Coefficient (Std. Err.)	Coefficient (Std. Err.)	Coefficient (Std. Err.)	Coefficient (Std. Err.)	Coefficient (Std. Err.)
Age 26-30	3.1530	-0.2502	-0.0104	-0.0253	-0.0444	0.0373
	(1.6704)	(0.0484)	(0.0114)	(0.0078)	(0.0091)	(0.0431)
Age 31-35	4.3346	-0.4162	-0.0237	-0.0527	-0.0795	0.0736
	(3.0820)	(0.0894)	(0.0210)	(0.0144)	(0.0168)	(0.0795)
Age 36-40	6.2992	-0.4728	-0.0252	-0.0649	-0.1075	0.1288
	(4.5461)	(0.1318)	(0.0310)	(0.0213)	(0.0248)	(0.1173)
Age 41-45	9.2366	-0.4635	-0.0257	-0.0723	-0.1376	0.2064
	(6.0255)	(0.1748)	(0.0410)	(0.0282)	(0.0329)	(0.1554)
Age 46-50	14.3750	-0.4013	-0.0217	-0.0748	-0.1627	0.2757
	(7.5116)	(0.2179)	(0.0512)	(0.0352)	(0.0410)	(0.1938)
Age 51-55	22.9203	-0.2301	0.0066	-0.0596	-0.1764	0.3244
	(8.9988)	(0.2610)	(0.0613)	(0.0422)	(0.0492)	(0.2321)
Age 56-60	26.6339	-0.0017	0.0648	-0.0226	-0.1807	0.3352
	(10.4863)	(0.3041)	(0.0714)	(0.0492)	(0.0573)	(0.2705)
Age 61-65	11.8668	0.2500	0.1222	0.0401	-0.1774	0.3048
	(12.0468)	(0.3494)	(0.0821)	(0.0565)	(0.0658)	(0.3108)
(Low-ed=1)*trend	0.2640	-0.0015	0.0000	-0.0002	-0.0005	-0.0006
	(0.1057)	(0.0031)	(0.0007)	(0.0005)	(0.0006)	(0.0027)
(Middle-ed=1)*trend	0.0801	0.0006	-0.0003	-0.0001	-0.0003	0.0004
	(0.1053)	(0.0031)	(0.0007)	(0.0005)	(0.0006)	(0.0027)
(High-ed=1)*trend	0.0716	-0.0070	0.0000	-0.0009	-0.0024	0.0024
	(0.1054)	(0.0031)	(0.0007)	(0.0005)	(0.0006)	(0.0027)
(Male=1)*trend	-0.0967	-0.0187	0.0006	0.0014	-0.0137	0.0674
	(1.1969)	(0.0347)	(0.0082)	(0.0056)	(0.0065)	(0.0309)
(Female=1)*trend	0.0049	-0.0158	0.0012	0.0029	-0.0146	0.0695
	(1.1968)	(0.0347)	(0.0082)	(0.0056)	(0.0065)	(0.0309)
Employment composition:						
	-182.9275	-5.5467	-0.9715	0.0778	4.3531	-6.4174
(Age<=25)*(No-ed or Low-ed)	(191.0375)	(5.5405)	(1.3014)	(0.8956)	(1.0437)	(4.9283)
(26<=Age<=40) * (No-ed or	-171.5059	-4.1224	-0.9771	0.0188	4.3105	-7.1606
Low-ed)	(185.8118)	(5.3890)	(1.2658)	(0.8711)	(1.0151)	(4.7935)
(41<=Age<=50)* (No-ed or	189.2101	-7.8002	1.3642	0.0059	3.2344	-3.4098
Low-ed)	(309.7236)	(8.9827)	(2.1099)	(1.4521)	(1.6921)	(7.9901)
	-143.2488	-8.5651	-1.0808	0.3819	5.7501	-3.5887
(51<=Age)*(No-ed or Low-ed)	(300.7875)	(8.7235)	(2.0490)	(1.4102)	(1.6433)	(7.7595)
(Age<=25)*(Mid-ed or High-	-112.5373	-5.3083	-0.9390	-0.0093	2.7575	-3.0255
ed)	(176.9090)	(5.1308)	(1.2052)	(0.8294)	(0.9665)	(4.5638)
(26<=Age<=40)* (Mid-ed or	-81.4482	-5.4591	-0.8553	0.1912	3.1717	-1.6893
High-ed)	(172.5482)	(5.0043)	(1.1754)	(0.8090)	(0.9427)	(4.4513)
(41<=Age<=50)* (Mid-ed or	-328.1472	-7.3028	-1.9619	0.1450	7.2255	-12.0684
High-ed)	(260.0783)	(7.5429)	(1.7717)	(1.2193)	(1.4209)	(6.7093)
GDP growth rate (per capita)	-91.1455	-0.6757	-0.3308	-0.1691	-0.7970	-0.7465
	(46.9103)	(1.3605)	(0.3196)	(0.2199)	(0.2563)	(1.2102)
Unemployment rate	1.4695	-0.0254	0.0044	-0.0009	-0.0007	0.0555
	(1.3156)	(0.0382)	(0.0090)	(0.0062)	(0.0072)	(0.0339)
Minimum wage growth rate	-11.8984	-2.5606	-0.3394	0.0904	1.0425	0.4504
	(45.4736)	(1.3188)	(0.3098)	(0.2132)	(0.2484)	(1.1731)
Inflation rate	-39.8752	0.3347	-0.3907	-0.0911	-0.9112	1.6683
	(44.1426)	(1.2802)	(0.3007)	(0.2070)	(0.2412)	(1.1388)
R-Square	0.7717	0.8104	0.6411	0.7611	0.5976	0.4225

Notes: Source DADS-EDP, 868 observations (1967-1999)

Table 5: Analysis of the Fixed Cell Effects

Mobility Indices Fixed Effects:	Minus Chi-Square	Per Capita Decile Movement	Per Capita Share Movement	Per Cap.non Directional Change in Logs	Per Capita Directional Change in Logs	Fields-Theil Index
	Coefficient (Std. Err.)	Coefficient (Std. Err.)	Coefficient (Std. Err.)	Coefficient (Std. Err.)	Coefficient (Std. Err.)	Coefficient (Std. Err.)
Constant	82.4457	9.4055	0.8489	-0.1157	-2.6398	-1.6614
	(4.4102)	(0.0588)	(0.0128)	(0.0109)	(0.0139)	(0.0544)
Male	7.0182	0.3006	0.0499	0.1237	-0.0837	0.1760
	(2.2291)	(0.0297)	(0.0064)	(0.0055)	(0.0070)	(0.0275)
Low-education	-23.8824	0.0654	0.0067	0.0107	0.0514	-0.0005
	(3.1071)	(0.0414)	(0.0090)	(0.0077)	(0.0098)	(0.0383)
Middle-education	-12.6664	-0.1821	0.0268	0.0052	0.0313	-0.1060
	(3.1466)	(0.0419)	(0.0091)	(0.0078)	(0.0099)	(0.0388)
High-education	-22.8100	0.4647	0.0209	0.0901	0.2368	-0.2683
	(3.1466)	(0.0419)	(0.0091)	(0.0078)	(0.0099)	(0.0388)
Born in 1917-1921	-38.4650	-1.1607	-0.0848	-0.0583	0.1519	-0.8209
	(5.8372)	(0.0778)	(0.0169)	(0.0145)	(0.0184)	(0.0720)
1922-1926	-44.9704	-1.0620	-0.0956	-0.0276	0.1705	-0.8635
	(5.3816)	(0.0717)	(0.0156)	(0.0133)	(0.0170)	(0.0664)
1927-1931	-43.3095	-1.1198	-0.1324	-0.0592	0.1066	-0.7090
	(5.3816)	(0.0717)	(0.0156)	(0.0133)	(0.0170)	(0.0664)
1932-1936	-34.1694	-1.0448	-0.1279	-0.0691	0.0925	-0.6381
	(5.3816)	(0.0717)	(0.0156)	(0.0133)	(0.0170)	(0.0664)
1937-1941	-28.0387	-0.9290	-0.1229	-0.0696	0.0804	-0.5466
	(5.3816)	(0.0717)	(0.0156)	(0.0133)	(0.0170)	(0.0664)
1942-1946	-22.3874	-0.8957	-0.1177	-0.0751	0.0594	-0.4747
	(5.3816)	(0.0717)	(0.0156)	(0.0133)	(0.0170)	(0.0664)
1947-1951	-15.8422	-0.7915	-0.1158	-0.0777	0.0413	-0.4000
	(5.3816)	(0.0717)	(0.0156)	(0.0133)	(0.0170)	(0.0664)
1952-1956	-8.8947	-0.7047	-0.1137	-0.0792	0.0226	-0.3202
	(5.3816)	(0.0717)	(0.0156)	(0.0133)	(0.0170)	(0.0664)
1957-1961	-4.5045	-0.6509	-0.1052	-0.0784	0.0007	-0.2633
	(5.3816)	(0.0717)	(0.0156)	(0.0133)	(0.0170)	(0.0664)
1962-1966	0.5484	-0.5768	-0.0894	-0.0700	-0.0160	-0.2228
	(5.3816)	(0.0717)	(0.0156)	(0.0133)	(0.0170)	(0.0664)
1967-1971	12.7349	-0.2738	-0.0581	-0.0493	-0.0310	-0.1165
	(5.3816)	(0.0717)	(0.0156)	(0.0133)	(0.0170)	(0.0664)
R-Square	0.8216	0.9190	0.7125	0.9053	0.9361	0.8581

Notes: Source: DADS-EDP, 94 observations

Omitted education group is "no known diploma", omitted birth cohort is "1912-1916"

Table 6: Correlations Across Aggregate Mobility Indices

Aggregate Correlation	Minus Chi Square	Per Capita Centile Movement	Per Capita Share Movement	Per Cap.non Directional Change in Logs	Per Capita Directional Change in Logs	Fields-Theil Index
Minus Chi Square	1.0000	0.9160	0.9257	0.9476	0.8797	0.5693
Per Capita Centile Movement	0.9160	1.0000	0.8601	0.8846	0.8068	0.5711
Per Capita Share Movement	0.9257	0.8601	1.0000	0.9452	0.8950	0.5550
Per Capita non Directional Change in Logs	0.9476	0.8846	0.9452	1.0000	0.9740	0.5959
Per Capita Directional Change in Logs	0.8797	0.8068	0.8950	0.9740	1.0000	0.5499
Fields-Theil Index	0.5693	0.5711	0.5550	0.5959	0.5499	1.0000

Notes: Source:DADS-EDP, 31 observations

Table 7: Correlations Across the Cell-Level Mobility Indices

Correlation between Cells	Minus Chi Square	Per Capita Decile Movement	Per Capita Share Movement	Per Cap.non Directional Change in Logs	Per Capita Directional Change in Logs	Fields-Theil Index
Minus Chi Square	1.0000	0.4698	-0.0224	0.1206	0.0887	0.3132
Per Capita Decile Movement	0.4698	1.0000	0.5342	0.7409	0.4763	0.1228
Per Capita Share Movement	-0.0224	0.5342	1.0000	0.8705	0.4377	-0.3850
Per Capita non Directional Change in Logs	0.1206	0.7409	0.8705	1.0000	0.5230	-0.1526
Per Capita Directional Change in Logs	0.0887	0.4763	0.4377	0.5230	1.0000	-0.1951
Fields-Theil Index	0.3132	0.1228	-0.3850	-0.1526	-0.1951	1.0000

Notes: Source:DADS-EDP, 868 observations. One observation is a cell-year. Observations included in the analysis have strictly more than 10 individual observations. A cell is the interaction of a sex, an education group, and a cohort. The analysis period is 1967-1999. All indices are within-cell computations.

Table 8: Correlations Across the Mobility Indices Fixed-Effects

Correlation between Fixed Effects	Minus Chi Square	Per Capita Decile Movement	Per Capita Share Movement	Per Cap.non Directional Change in Logs	Per Capita Directional Change in Logs	Fields-Theil Index
Minus Chi Square	1.0000 0.0000	0.4644 0.0001	0.2946 0.0039	0.0176 0.8662	-0.6759 0.0001	0.7546 0.0001
Per Capita Decile Movement	0.4644 0.0001	1.0000 0.0000	0.6019 0.0001	0.6455 0.0001	-0.0456 0.6626	0.5585 0.0001
Per Capita Share Movement	0.2946 0.0039	0.6019 0.0001	1.0000 0.0000	0.6588 0.0001	-0.2230 0.0308	0.3356 0.0009
Per Capita non Directional Change in Logs	0.0176 0.8662	0.6455 0.0001	0.6588 0.0001	1.0000 0.0000	0.1016 0.3296	0.1296 0.2132
Per Capita Directional Change in Logs	-0.6759 0.0001	-0.0456 0.6626	-0.2230 0.0308	0.1016 0.3296	1.0000 0.0000	-0.7604 0.0001
Fields-Theil Index	0.7546 0.0001	0.5585 0.0001	0.3356 0.0009	0.1296 0.2132	-0.7604 0.0001	1.0000 0.0000

Notes: Source DADS-EDP, 94 observations. Each observation corresponds to one group sex-education-cohort.