# Trends in Occupational Mobility in France: 1982-2009[☆]

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**Abstract**

Are labor markets more turbulent now than thirty years ago? Most job and worker flows imply that the answer is "no", with one exception: occupational mobility, which increased substantially in the United States. This paper remedies the lack of comparable evidence by focusing on France for the years 1982 to 2009. After correcting for various statistical biases and discrepancies that affect the measurement of occupational mobility, it documents this reallocation process overall and in different subgroups. The data reveal that, over the period considered, the fraction of workers switching occupation exhibits no trend in the aggregate because changing demographics mask increases in mobility within several age and education groups. After taking these composition effects into account, occupational mobility increased sharply in France as well.

*Keywords:* Occupational Mobility, Worker Mobility, Measurement Error

## 1. Introduction

There is an active debate on whether labor markets are subjected to more disturbances now than thirty years ago. The question remains controversial, notably because of conflicting empirical evidence. Indeed, most job and worker flows in Europe and in the United States are remarkably flat[1]. The only exception is in the fraction of workers switching occupation which rose substantially in the US, as shown by Kambourov and Manovskii (2008). Similar empirical evidence is lacking for Europe[2]. The purpose of the present paper is to fill part of this gap by documenting worker mobility across occupations in France. The main message can be summarized as follows: there is no significant trend in overall mobility over the years 1982 to 2009 because composition effects due to demographic changes offset increases in mobility within several age and education groups. After taking these effects into account, occupational mobility increased sharply in France as well.

Recent empirical evidence suggests that characterizing worker flows across occupations is of crucial importance for our understanding of the functioning of labor markets. To the extent that human capital may be industry- (Neal, 1995 and Parent, 2000) or occupation- (Kambourov and Manovskii, 2009) specific, a substantial amount of accumulated skills may be destroyed upon occupational switches. The reallocation process of workers across occupations may thus be relevant to a variety of researched areas, ranging from changes in wage inequality to the debates on job stability and security (see Autor and Katz (1999) for a survey of the literature on the former topic and the 1999 special issue of the Journal of Labor Economics regarding the latter).

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[1]Davis et al. (2006) for instance, find no increase in job destruction rates and in gross flows between unemployment and employment in the United States since the 1980s. Over the same period, Davis (2008) shows that the risk of unwanted job losses declined sharply.

[2]The only study of occupational mobility in Europe I am aware of is that of Longhi and Brynin (2010) who compare Germany and the United Kingdom with data from the British Household Panel Survey (BHPS) and the 'West' German sample of the German Socio-Economic Panel (GSOEP). However, their focus is on the individual determinants of occupational switches, not on the dynamics of mobility. They only report the levels of occupational mobility in these two countries.

Documenting occupational mobility is also important from a public policy standpoint. In order to fight against unemployment, several countries have implemented programs to redeploy workers who lost their jobs, help them to search for work elsewhere or to retrain for other jobs. Hence the relevance of studying whether labor market experiences are more disruptive now than thirty years ago, as argued by Ljungqvist and Sargent (2008). Occupational mobility has the potential to highlight this question and therefore to reveal crucial information for the debates in Europe surrounding labor market reforms.

As one of the largest economy in Europe, France is a particularly interesting candidate to study occupational mobility. First, the French labor market underwent the significant changes in employment experiences that affected most economies in the continent during the past decades (see e.g. Blanchard, 2006). Thus, what can be learned from mobility in France is likely to be relevant for other European countries as well. Second, France's labor market is reputed to be rigid and characterized by some of the institutional features that the conventional wisdom, in the words of Nickell (1997), blames for the poor employment performances in Europe. It is thus natural to ask how different mobility in France and in the more flexible American labor market is.

This paper uses the 1982 to 2009 waves of the representative French Labor Force surveys (FLFS), the *Enquête Emploi*, to measure occupational mobility, defined as the fraction of currently employed individuals who report a current occupation different from their most recent previous report of an occupation[3]. It documents the levels and trends of occupational mobility. The large size of the sample makes it possible to study occupational mobility within different age, education and gender groups to emphasize both changes in mobility within these groups, between these groups and how they affect the measurement of mobility in the aggregate.

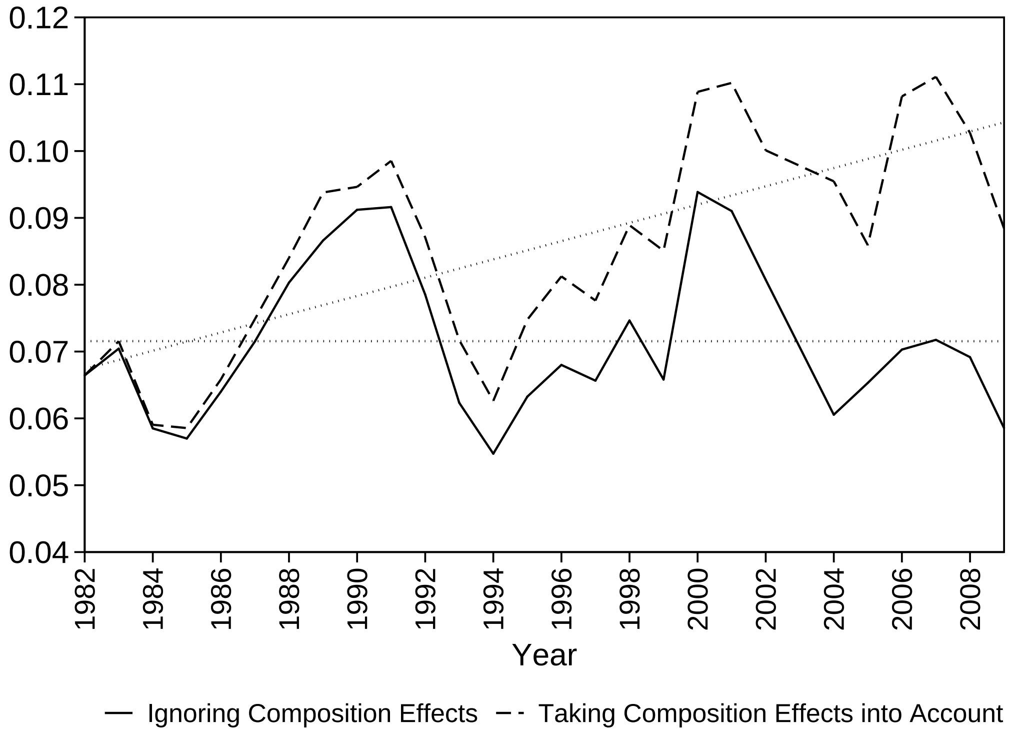
A substantive part of the analysis is to correct for various statistical biases and discrepancies that affect the measurement of occupational mobility. Indeed occupation affiliation is error-prone, which may bias the estimates of mobility rates. Moreover, methodological breaks affect the data collection in several dimensions and cannot be ignored to obtain consistent time series for the whole period. This paper discusses different potential sources of coding errors, document their consequences and implement correction strategies. The results obtained after implementing these correction strategies are robust to various tests.

The main finding of the analysis is depicted in figure 1. When changes to the age and education characteristics of the population in employment are ignored (solid line), the figure indicates that aggregate mobility in France is low – about 7.4% of employed persons – and exhibits no overall trend. A very different picture emerges when these changes are taken into account (dashed line): occupational mobility increased from roughly 6% to an average of 10% – almost a twofold increase.

Why are these composition effects so large? There are two reasons for this. First, the levels of mobility in France are low, and thus even modest changes to the relative size of age and education groups are sufficient to mask increases in mobility within these groups. Second, the composition effects are mostly due to the aging of the population of employment, not to its increasing educational attainment levels. Since mobility decreases sharply with age, holding the age structure of the population in employment unchanged throughout the period when re-aggregating the data generates the steep increase in mobility depicted in figure 1.

The findings regarding the levels of occupational mobility stand in sharp contrast with the results for the United States. Indeed, Kambourov and Manovskii (2008), Moscarini and Thomsson (2007) and Parrado et al. (2007) all report levels of mobility in the US that are about two to three times higher. Similar contrasts appear between the United Kingdom and Germany (Longhi and Brynin, 2010), with levels of mobility in the latter

[3]For example, an individual employed in two consecutive years would be considered as switching occupations if she reports a current occupation different from the one she reported in the previous year. If an individual is employed in the current year, but was unemployed in the previous year, a switch in her occupation will be recorded if she reports a current occupation different from the one she reported when she was most recently employed. This is the definition adopted by Kambourov and Manovskii (2008).




NOTE: Occupational mobility at the three-digit level (fraction of workers in employment), individuals of working-age who are full time workers (not self-) employed in the private sector. See the text for the calculation of occupational mobility. The horizontal (resp. upward-slopping) dotted line is the prediction from a linear regression of the solid (resp. dashed) line against a constant and a time-trend. The dashed line is obtained after reweighting individual observations to hold the population structure unchanged since 1982. This reweighting procedure is detailed in footnote 15.

Figure 1: Trends in Occupational Mobility in France, 1982-2009: The Role of Composition Effects

country similar to those in France. Despite these large differences in levels, the analysis also reveals a number of similar findings. For instance worker churning across occupations (as measured by the difference between gross flows and net flows[4]) accounts for two-thirds of total occupational mobility in France and in the United States as well.

Turning to the trends in occupational mobility, the importance of adjusting for composition effects is worth emphasizing. Kambourov and Manovskii (2008) perform a similar exercise and find that this adjustment inflates the increase in mobility by "only" 10 percentage points. By contrast – and regardless of the base year that is used to take into account composition effects–, measured mobility would have been higher by 25% by the late 2000s had the composition of the population in employment not changed. It is also important to note that composition effects in France reflect mainly the natural aging of the population, and therefore that the increases in mobility for some age groups are likely to be independent of the changes in the relative size of these groups. For this reason it is appropriate to adjust for composition effects.

The paper is organized as follows. Section 2 describes the data and sample used in this paper. Section 3 analyzes the consequences of coding procedures and methodological changes in the FLFS on the measurement of occupational mobility. Two correction procedures to obtain consistent time series of occupational mobility are subsequently developed in section 4. Section 5 characterizes the patterns of occupational mobility overall and section 6 analyzes these patterns within age, education and gender groups. Section 7 re-aggregates these within-groups series while taking into account changes in their relative size to quantify the importance of composition effects. Section 8 concludes.

[4]Net mobility is defined as (one-half of) the sum of the absolute changes in occupational employment shares.

## 2. Data and Sample

*The French Labor Force Survey*

This paper uses data from the 1982 to 2009 waves of the French Labor Force Survey (FLFS) collected by the French National Institute for Statistics and Economic Studies. The FLFS is a representative sample of the French labor force. This is the main source for unemployment statistics in France, and is the most comprehensive dataset which records individuals' labor force experiences and occupational status over a long period of time. The FLFS is a rotative panel. From 1982 to 2002, interviews were carried out annually and individuals were surveyed (at most) three consecutive years. In 2003 the FLFS was transformed to a quarterly rotative panel in which individuals are surveyed (at most) six consecutive quarters.

The panel dimension of the FLFS makes it possible to compare individuals' employment status for year $t$ and year $t-1$, thus making it possible to study labor market transition over a one-year window. The FLFS also asks individuals who enter the sample during year $t$ about their employment status at $t-1$. For those already in the sample at $t-1$ information is retrieved from their past record and matched with their interview for year $t$. I will document below the consequences of these different techniques to the data collection.

There have been two major methodological changes in the FLFS over the period under study. The first change took place in 1990 when the sample was renewed. This was accompanied by changes to the questionnaire and a switch to computer assisted classification of occupations. Instructions given to interviewers also changed (see AppendixA). The second and more important change took place in 2003 with the transformation from an annual rotating panel to a quarterly one. This coincided with changes to the questionnaire and an update of the occupational classification.

*Sample disposition*

This paper focuses on civilians of working age (16 to 64 years old) who (i) have been in the labor force for at least a year[5], (ii) are full-time workers employed in the private sector[6] and (iii) are not self-employed or helping a family member without having employee status. Occasionally, some of these sample restrictions are dropped to include, say, part-time workers in order to gauge the sensitivity of the results to alternative sample dispositions. These sensitivity checks are explicitly indicated in the text.

I impose some further sample restrictions and drop a small number of observations for which I lack relevant information. Specifically, I drop observations for which it is not possible to establish whether they satisfy criterion (i) above. Moreover for those in employment I discard observations for which it is not possible to establish whether criteria (ii) and (iii) are met. I also drop employed persons with a missing occupational code of the job held. Finally I drop a handful of observations for which information about the highest diploma obtained by the individual is missing[7]. These successive sample restrictions leave me with a baseline sample of 58,389 observations a year on average. As explained in the next section, one-half of this baseline sample will be used throughout the analysis.

[5]Requiring individuals to be in the labor force for at least a year dismisses concerns regarding the treatment of school-to-work transitions. Moreover individuals surveyed in the FLFS are asked precisely whether they have already been in the labor force: summer jobs for instance are explicitly mentioned as being not a valid labor market experience.

[6]The primary reason for excluding government workers from the baseline sample is that mobility in the public sector is restricted by specific rules such as automatic promotion based on tenure. Changes in mobility for these workers could therefore stem from modifications to this legislative framework rather than reflect trends in market forces.

[7]Throughout the analysis education levels are grouped into four categories: individuals with no diplomas fall into the *low* education category; individuals who have not reached the 'baccalaureat' fall into the *medium* education category; individuals whose highest diploma is the baccalaureat fall into the *high* education category; finally individuals who studied more than two years after the baccalaureat fall into the *very high* education category. This split of the workforce by educational attainment allows one to obtain groups comparable in size over time, that can be consistently tracked over time and that are large enough to avoid "small cell" problems when disaggregating the data.

## 3. Occupational Coding in the FLFS

The French Statistical Institute defines occupations up to 4 digits. In the FLFS, occupations at the one and two-digit levels are used to code answers to several questions about a worker's trajectory on the labor market while occupations at the four-digit level are available only to describe one's current and past occupations of employment[8]. Because of the higher reliability of the one- and two-digit level and the very similar results that one obtains when focusing either on the three- and four-digit level, I restrict attention to the one, two and four-digit levels. With a slight abuse of language, I refer to the latter as the "three-digit level" to indicate that it is the higher level of disaggregation used in the analysis[9].

*Dependent vs. Independent Coding*

Figure 2 illustrates how the occupation of employment at the time of the interview ($P_t$) and that of the job held one period before ($PP_t$) are coded in wave $t$ of the FLFS. Highlighting these coding procedures is important as they are likely to generate a large amount of measurement error in occupation affiliation (see e.g. Mellow and Sider (1983) and Kambourov and Manovskii (2010) for related discussions). In particular, dependent coding is more reliable to identify genuine labor-market transitions. Mathiowetz (1992) for instance reports that there are four times less disagreement between two codes of employee's records when these codes are assigned simultaneously than when they are assigned independently. Regarding the FLFS:

- In the 1982 to 2002 waves for first-interviewed individuals, even if $P_t$ is coded with error, $PP_t$ is likely to be affected by the same coding error if the individual did not switch occupation and an occupational change will therefore not be recorded. On the contrary, the individual's record of $PP_{t+1}$ for the second interview will be retrieved from the (potentially miscoded) occupation $P_t$. The measurement error transits to the second record and a (false) occupational change is thus much more likely to be recorded.

- In the 2003 to 2009 waves, the opposite is true: for first-interviewed individuals the comparison of $P_t$ and $PP_t$ will be affected by the fact that the two codes are assigned independently. On the other hand for re-interviewed individuals $P_{t+1}$ is always coded with explicit reference to $P_t$ and I am therefore more likely to identify genuine switches for these individuals only.

Figure 3 plots the time series of occupational mobility for those employed in two consecutive years. It is clear that the coding procedures of the survey affect measured occupational mobility. Mobility is always higher among individuals with independently coded occupations: this corresponds to re-interviewed individuals in the 1982 to 2002 waves and first-interviewed individuals in the waves from 2003 onwards. On the other hand there is no evidence of systematic breaks for individuals with dependently coded occupations of employment.

Consistently with this discussion of coding procedures, I restrict the analysis to individuals with dependently assigned occupational codes. Of course, a drawback of this restriction comes from sample attrition, which is likely to be endogenous to mobility decisions. Therefore I adjust individual weights for sample attrition[10]. The sample of re-interviewed individuals as well as the richer post-2003 survey will serve to consolidate the results (details follow).

[8]For instance currently unemployed persons are asked about their last occupation of employment and the occupation of employment of their longest employment spell. They are also asked about the occupation in which they would like to find a job. The answers to these questions are coded into one and two-digit codes only.

[9]Examples of occupations at the finest level of the classification include truck farmers, taxi drivers, architects, social workers, telephone operators, storekeepers. etc. At the most aggregated level, I break the two categories [administrative, sales and service occupations] and [manual laborers] into finer occupational categories by distinguishing skilled and unskilled jobs in these broad occupational groups. Thus, there are 7 categories at the one-digit level, 28 at the two-digit level and 434 at the three-digit level.

[10]The procedure to adjust the weights for re-interviewed individuals is similar to the procedure that I use in section 7 to re-weight individual observations to hold constant the demographic structure of the population in employment (see footnote 15). The only

*1982 to 2002 waves*

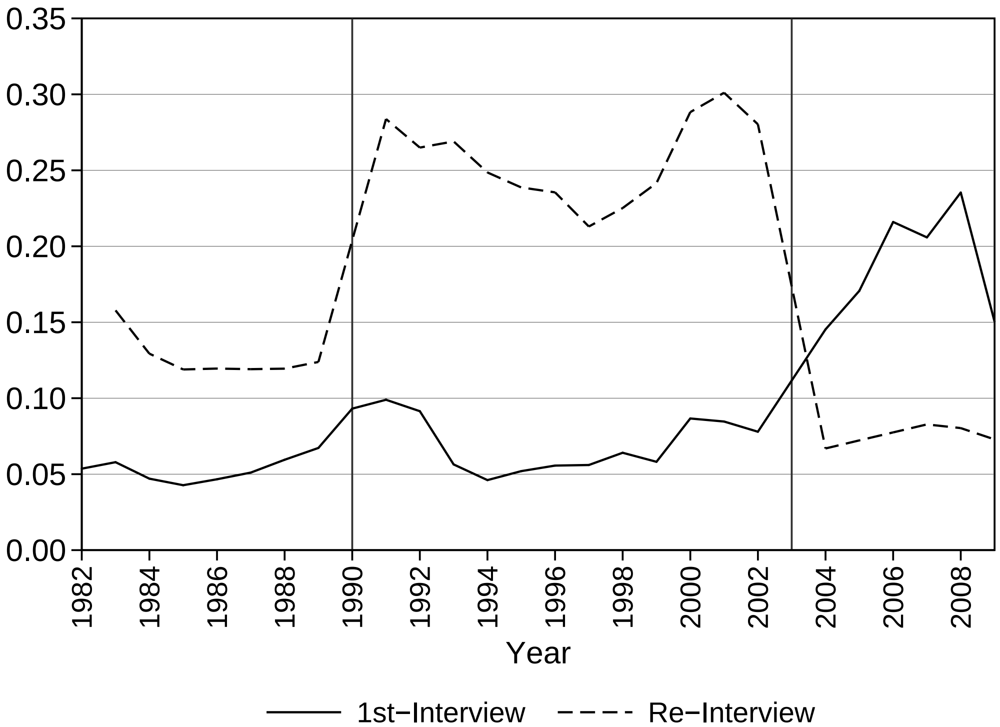
| 1st Interview at $t$ | | Re-interview at $t+1$ | |
|---|---|---|---|
| $PP_t$ | $P_t$ | $PP_{t+1}$ | $P_{t+1}$ |
| Dependent coding | Independent coding | $= P_t$ | Independent coding |

*2003 to 2009 waves*

| 1st Interview at $t$ | | Re-interview at $t+1$ | |
|---|---|---|---|
| $PP_t$ | $P_t$ | $PP_{t+1}$ | $P_{t+1}$ |
| Independent coding | Independent coding | $= P_t$ | Dependent coding |

NOTE: $P$ is the occupation of employment of the individual at the time of the interview and $PP$ is the previous occupation of employment. $t$ is the time at which the respondent enters the FLFS sample. The time horizon is one year in the 1982 to 2002 waves and one quarter in the 2003 to 2009 waves. In the 1982 to 2002 waves of the FLFS, $PP_t$ is dependently coded with an explicit reference made by the interviewer to $P_t$. From 2003 onwards, $P_{t+1}$ is dependently coded with an explicit reference made to $P_t$. See AppendixA for a description of these explicit references in the 1982-1989, 1990-2002 and 2003-2009 waves of the FLFS.

Figure 2: Dependent vs. Independent Coding of Occupations in the FLFS




NOTE: The figure reports the fraction of individuals with a current occupation of employment ($P$ in the language of figure 2) different from the previous one ($PP$ in the language of figure 2). The vertical lines indicate the 1990 and 2003 methodological changes. The sample is restricted to individuals employed in two consecutive years. Individual weights are adjusted for sample attrition (see footnote 10 for details).

Figure 3: Apparent Occupational Mobility (three-digit): 1st-interviewed and re-interviewed Individuals

*The 2003 Update of Occupational Codes*

In 2003, the French Statistical Institute updated the four-digit level of the occupational classification. In principle the new classification allows to track a larger amount of mobility because some empty occupation cells are merged with others while some cells that contain many individuals are broken down into several smaller cells. This raises a concern about the comparability of mobility rates across the different waves of the FLFS.

Changes seemed however minor, as the following experiment illustrates. In 2006, the French Statistical Institute released a version of the 2003 file in which both the 1982 and 2003 codes are available. These codes are available not only for the current and previous occupations of employment, but also for the occupation of the first job held by the individual in his/her current company. This allows me to compare different mobility rates computed with either the 1982 or the 2003 codes.

Table 1 reports these mobility rates as a function of workers' tenure. It also displays two types of "errors" in the language of statistical testing: "Error type I" refers to the fraction of "movers" according to the 1982 codes among those recorded as "stayers" in the 2003 classification while "Error type II" is the fraction of "stayers" according to the 1982 codes among "movers" in the 2003 classification. It is clear that there is no significant divergence between mobility rates as revealed by the 1982 and the 2003 codes. Indeed, even if "Error type II" increases with a worker's tenure, annual mobility rates also drop sharply, which implies that these errors are committed only for a very small share of the population. For example the probability of error type II for individuals with more than 10 years of tenure is equal to 0.114x0.025 = 0.003. For this reason adjusting gross mobility rates computed with the 2003 occupational classification does not seem necessary[11]. The time series reported hereafter confirm that there is not need to adjust the post-2003 rates on their pre-2003 counterparts.

*Other Measurement Issues*

There are two other issues that might affect the measurement of occupational mobility. First, dependent coding does not eradicate all errors in occupational affiliations. Controlling for misclassification is thus necessary. To do so, I will follow a cleaning procedure similar to that of Moscarini and Thomsson (2007). Second, for individuals who were unemployed one period before, information about the occupation of employment before the unemployment spell is missing. For these individuals (about 3% of total employment in each year), I will infer mobility from a sample of re-interviewed individuals who experienced a period of unemployment and whose occupation of employment is observed both before and after the unemployment spell. Both correction strategies are described in greater details in section 4.

Another possible issue is the time horizon over which mobility is measured with the retrospective question asked to first-interviewed individuals. For instance Kambourov and Manovskii (2010) show that retrospective questions cause the March supplement to the Current Population Survey (CPS) to measure mobility over a horizon shorter than one year (possibly two to three months only). For a number of reasons I do not think that this issue arises with the FLFS data. First the survey questions unambiguously refer by name, to the month one year before the interview. Second, in 1990 and in 1999, the FLFS was carried out in January. If my estimates for the other years were only to reflect mobility over a shorter time horizon, then I would find markedly different levels of mobility compared to 1990 and 1999, which is not what figure 3 reveals. Third, the post-2003 quarterly survey allows me to calculate mobility with respect to different time horizons and these calculations confirm the levels of occupational mobility calculated over a one-year window.

difference when I adjust for sample attrition is that the probability estimated in the first stage is that of being re-interviewed. Thus the dependent variable is the indicator that takes the value of one if the individual is re-interviewed and 0 otherwise. The probability is estimated separately for each wave of the FLFS in which there are both first-interviewed and re-interviewed individuals.

[11]Net mobility rates on the other hand are affected by the 2003 update of the occupational classification. In subsection 5.2 I explain how I align the three-digit levels of net mobility after 2003 on their pre-2003 counterparts.

Table 1: Comparison of Mobility Rates computed with the 1982 and 2003 Occupational Codes

| Tenure | Mobility over the past year (%) | | | | Mobility since entry in the firm (%) | | | |
|---|---|---|---|---|---|---|---|---|
| | 1982 Code | 2003 Code | Error Type I | Error Type II | 1982 Code | 2003 Code | Error Type I | Error Type II |
| < 1 year | 39.83 | 40.44 | 0.00 | 0.79 | 0.68 | 0.68 | 0.00 | 0.00 |
| | (0.24) | (0.24) | (0.00) | (0.07) | (0.04) | (0.04) | (0.00) | (0.00) |
| 1-2 years | 2.95 | 2.75 | 0.21 | 0.00 | 1.20 | 1.20 | 0.00 | 0.00 |
| | (0.05) | (0.05) | (0.01) | (0.00) | (0.03) | (0.03) | (0.00) | (0.00) |
| 2-5 years | 3.21 | 3.17 | 0.28 | 6.98 | 12.10 | 12.21 | 0.67 | 5.77 |
| | (0.03) | (0.03) | (0.01) | (0.26) | (0.06) | (0.06) | (0.02) | (0.12) |
| 5-10 years | 1.97 | 2.45 | 0.00 | 19.80 | 21.29 | 22.18 | 0.39 | 5.40 |
| | (0.04) | (0.04) | (0.00) | (0.66) | (0.11) | (0.11) | (0.02) | (0.13) |
| > 10 years | 2.36 | 2.50 | 0.15 | 11.39 | 39.55 | 40.36 | 1.17 | 3.69 |
| | (0.02) | (0.02) | (0.01) | (0.30) | (0.07) | (0.07) | (0.02) | (0.05) |

NOTE: The calculation are based on the 2006 release of the 2003 wave of the FLFS after adopting the sample disposition described in section 2. "Error type I" is the fraction of "movers" according to the 1982 codes among those recorded as "stayers" in the 2003 classification while "Error type II" is the fraction of "stayers" according to the 1982 codes among "movers" in the 2003 classification. The figures are expressed in percentage of the population in employment. Standard errors in parentheses.

## 4. Correction Procedures

*Cleaning procedure*

To identify genuine occupational switches for those who report a valid previous occupation, I rely on auxiliary information available in the FLFS. I consider an occupational switch at the three-digit level to be genuine when (i) the current occupation is different from the previous one and (ii) one observes either: (a) a change in employer or (b) no change in employer but a change in the classification of the job. AppendixB explains how these auxiliary variables are constructed. This cleaning procedure relies on the idea that individuals are less likely to be simultaneously misclassified as having switched occupation and employer or as having switched occupation and classification of the job if they did not change employer. For occupational switches at the one and two-digit levels on the other hand, I consider as spurious all switches that are not accompanied by a change in employer.

Table B1 (AppendixB) reports the results of this cleaning procedure. At the three-digit level, the procedure leads me to discard 16% of occupational switches in the 1982-1989 waves, 35% in the 1990-2002 waves and 52% in the post-2003 waves. At the one and two-digit levels, the figures range from 22 to 38% and are very similar for the 1982-1989 and 1990-2002 waves. Although these amounts of noise seem high, they are not unusual in the literature on measurement error, especially in the context of occupation affiliation. In the 1979-1993 files of the CPS for instance Moscarini and Thomsson (2007) show that (monthly) occupational mobility rates drop from 33.8% in the raw data to less than 4% when spurious labor market transitions are discarded. Kambourov and Manovskii (2008) report than 50% of occupation switches in the original files of the Panel Study of Income Dynamics (PSID) are due to coding error.

*Previously unemployed individuals*

To estimate the probability that a previously unemployed person switched occupation, I infer mobility from a sample of re-interviewed individuals who experienced a period of unemployment and whose occupation of employment is observed both before and after the unemployment spell. For these re-interviewed individuals, recording "wrong" occupational switches is unlikely since special attention is devoted to the record of occupation upon re-employment in the FLFS. For instance after 2003 a re-interviewed worker who experienced a spell of unemployment is asked the same series of questions as those in their first interview.

I postulate the following model:

$$\Pr\{\text{mob}_{it}=1|X_{it}\}=\Phi(X_{it}\beta) \tag{1}$$

where:

$$X_{it}\beta \quad = \quad \sum_j Educ_{j,i}\times\left(\beta_{0,j}+\beta_{1,j}age_i+\beta_{2,j}age_i^2+\beta_{3,j}time*age_i+\beta_{4,j}time*age_i^2\right) \tag{2}$$

In the above equation, $\text{mob}_{it}$ is a dummy variable that takes the value of one if individual $i$ reports an occupation for year $t$ different from his/her occupation before the unemployment spell, $time$ is a time trend, $Educ_j$ denotes educational dummies and $\Phi$ is the c.d.f. of the Normal distribution. The models are estimated at the different digit levels, separately for female and male workers. I then use the estimates from these models to predict mobility among previously unemployed individuals. The results of the estimation of (1) are reported in table C1 in AppendixC.

To understand how this affects the mobility rates reported hereafter, the last row of table C1 displays the predicted mobility at the mean of all variables. Focusing for instance on the two-digit level, a previously unemployed person has a '50-50' chance of switching occupation upon finding a job. Since re-entrants represent 3% of total employment on average over the period, taking them into account inflates mobility rates at the two-digit level by 1.5 percentage points. This allows me to express mobility rates as a percentage of total employment, not only as a percentage of those employed for two consecutive years.

## 5. Overall Mobility

### *5.1. Gross Mobility*

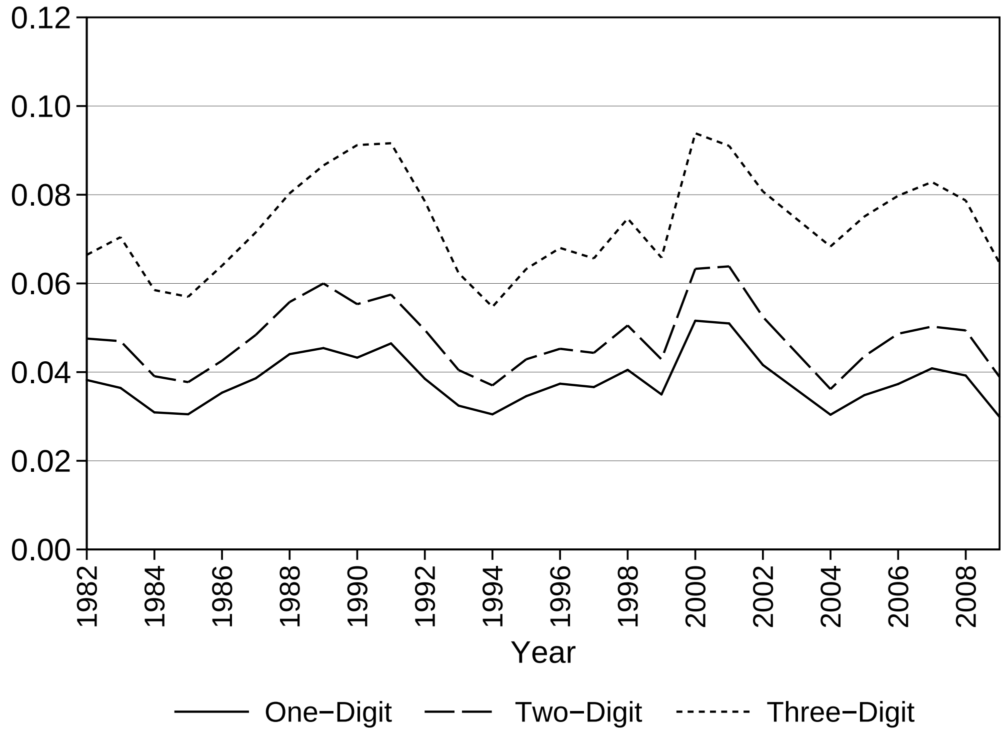
*Levels and trends*

Figure 4 plots the time series of occupational mobility obtained after implementing the correction procedures at the different digit levels. The main findings are as follows. First, on average over the 1982-2009 period, about 7.4% of all workers are employed in an occupation that differs from their most recent reported occupation. The corresponding figures at the one and two-digit levels are 3.8% and 4.7%, respectively. Second, a majority of occupational switches recorded at the most disaggregated level of the occupational classification occur at the two-digit level (the latter being very different from one another). Third, occupational mobility exhibits no overall trend over the period but may vary substantially from years to years. At the most disaggregated level for instance, occupational mobility rose from 6.7% in 1999 to a high of 9.4% the year after (a twofold increase).

How do these levels of occupational mobility compare with the countries where they have been documented along similar lines? In the United States, Kambourov and Manovskii (2008) find that occupational mobility averages 18% at the three-digit level of the Census occupation codes from the PSID. Moscarini and Thomsson (2007) confirm these high rates of occupation mobility: they show that in the CPS monthly mobility averages 3.5%[12]. Longhi and Brynin (2010) also find high rates of mobility in the United Kingdom: they report that the proportion of "stayers" over a time-horizon of one year is equal to 85% in the BHPS.

Differences in sample dispositions and in occupational codes used to identify mobility may account for some divergences between these high rates of mobility and those reported in figure 4, but probably not for the bulk of the 10 percentage points difference. For instance after adopting the same sample dispositions and

[12] However different at first sight, the figures from these two studies are similar for the overlapping period when one takes into account differences in definitions and sample restrictions as well as multiple occupational switches within a time horizon of one year.




NOTE: Occupational mobility at the different digit levels (fraction of workers in employment).

Figure 4: Occupational Mobility in France, 1982-2009: Different Digit Levels

occupational codes for Germany and the UK, Longhi and Brynin (2010) also report lower rates of mobility for Germany, where the proportion of "stayers" is equal to 93%. Thus, it is possible to conclude that mobility in France is low relative to countries with more liberal employment structures and that the magnitude of the gap in mobility rates between France and the US is a factor between two to three, similar to the differences in levels between the UK and Germany.

Differences in the levels of occupational mobility are important in the light of several actively researched questions, notably the findings on the specificity of human capital and the job security and stability debates. The findings of the present paper suggest higher worker attachment to their occupation of employment in France. This is in line, for instance, with Lefranc (2003)'s comparison of wage losses of displaced workers: his findings reveal that wage losses in France are a loss of accumulated human capital while in the US this is mostly due to downgrading of occupation. In the concluding remarks of the paper, I expand on some possible mechanisms behind these convergent empirical findings.

Another important difference with the United States is the absence of large significant time-trend in the series displayed in figure 4. Empirical debates surrounding economic turbulence account for the relevance of studying trends in aggregate mobility. Blanchard (2006) for instance concludes from his survey of different labor market flows that there is no evidence of increased turbulence. On the other hand Ljungqvist and Sargent (2008) argue that the substantial increase in industry and occupational mobility documented by Kambourov and Manovskii (2008) is compelling evidence in support of the opposite conclusion. Regarding France, figure 4 depicts only a moderate, marginally significant increase in the 2000s relative to 1990s, which suggests that the French labor market *as a whole* was not subjected to increased turbulence over the past three decades. However, in section 6 I show that this absence of upward trend in the aggregate masks significant changes within several sub-groups.

*Cyclical Patterns*

Investigating in details the interplay between occupational mobility and the business cycle is beyond the scope of the present paper. Meanwhile, a few remarks on the French macroeconomic context over the years 1982 to 2009 shed light on the cyclical patterns displayed by the time series of figure 4, particularly at the three-digit level. Indeed, the peaks in occupational mobility coincide with the two sub-periods of expansion (1988-1990 and 1997-2000) while mobility decreased following the two recessions of 1983 and 1993.

What type of occupational switches account for the cyclical patterns of the time series in figure 4? The bulk of those comes from switches that are accompanied by a change in employer. On average across years, they account for 55.8% of all occupational switches. This time series is highly volatile, with a standard deviation of 0.0085. This is slightly higher than the standard deviation of the (detrended) unemployment rate over the same period, which is equal to 0.0072. This time series is also negatively correlated with the unemployment rate. Within-firm occupational mobility, which accounts for roughly 20% of total mobility, is also negatively correlated with the unemployment rate but the correlation coefficient is marginally significant. On the other hand mobility upon re-entering employment is acyclical. These time series are also much less volatile than that of occupational switches accompanied by a change in employer[13].

This cyclical behavior of occupational mobility raises a number of questions. One is to quantify the extent to which switching occupation adds to the cyclicality of employer-to-employer transitions. Another one is to determine whether employer-to-employer transitions reflect primarily upward occupational mobility during economic expansions, in line with the idea that workers enjoy better career prospects during upturns. These are interesting avenues for future investigations.

Although I do not expand on the cyclical patterns of occupational mobility, this brief discussion confirms that it is procyclical, in line with the findings of Moscarini and Vella (2003) – though their inquiry is silent regarding the sources of this cyclicality (switches that are accompanied by a change in employer). Subsection 5.2 below shows that net mobility is pro-cyclical as well.

*Alternative Sample Dispositions and Measurements*

Are the time series displayed in figure 4 sensitive to the sample restrictions and the measurement of mobility adopted for most of the analysis? The next paragraphs discuss the levels and trends that would be obtained under alternative sample dispositions and restrictions regarding occupational switches that are considered as genuine.

Table 2 reports the levels and trends of mobility obtained after varying both: (i) the definition of total employment (along the columns of the table) and (ii) the measurement of mobility rates (along the rows of the table). Focusing first on the levels of mobility, table 2 shows that these are not significantly affected by alternative sample dispositions. For the three decades under study, mobility would be slightly lower if government workers were included in the sample and slightly higher if either part-time or self-employed workers were included in the definition of total employment. Yet, the differences with the baseline sample are always small – about one percentage point – and the trends in mobility are insensitive to alternative sample dispositions and measurements of occupational switches.

To save on space, the sensitivity analysis performed separately for male and female workers is not reported in table 2. However, it is clear that some sample restrictions are likely to affect the trends reported for both

[13]These calculations are my own. They are based on the annual time series of the unemployment rate retrieved from the French Statistical Institute. To detrend the unemployment rate I use a HP-filter with smoothing parameter equal to 100. The standard deviations of the time series of mobility upon re-entering employment and within-firm mobility are 0.0034 and 0.0035, respectively. The correlation coefficients between the unemployment rate and occupational mobility are equal to 0.055 (with a p-value of 0.785) for re-entry into employment, -0.902 (with a p-value lower than 0.001) for job-to-job mobility and -0.437 (with a p-value of 0.023) for within-firm mobility.

Table 2: Sensitivity of the Levels and Trends of Mobility to Sample Restrictions and Measurements of Mobility

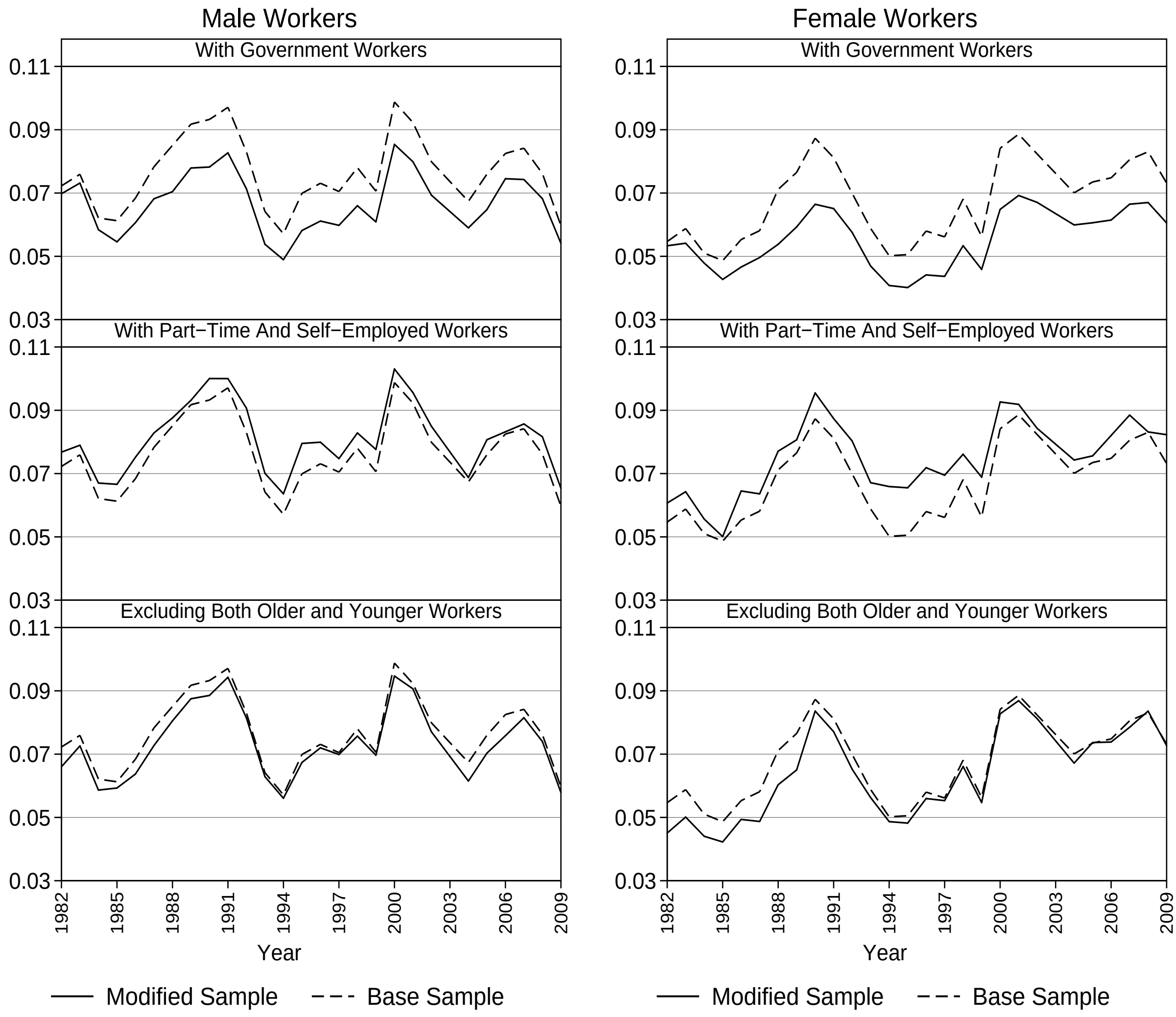
| | Average estimated mobility (%) | | | |
|---|---|---|---|---|
| | Base sample | Base sample + Government | Base Sample + Part-time | Base Sample + Self-employed |
| | **A. 1980's decade** | | | |
| Total Mobility (Raw series) | 6.94 | 6.08 | 7.15 | 7.20 |
| Discarding new entrants into employment | 5.75 | 5.14 | 5.85 | 6.08 |
| Discarding new entrants and within-firm mobility | 4.68 | 3.80 | 4.82 | 5.01 |
| | **B. 1990's decade** | | | |
| Total Mobility (Raw series) | 7.17 | 5.90 | 7.72 | 7.44 |
| Discarding new entrants into employment | 5.51 | 4.55 | 5.78 | 5.87 |
| Discarding new entrants and within-firm mobility | 4.40 | 3.60 | 4.70 | 4.45 |
| | **C. 2000's decade** | | | |
| Total Mobility (Raw series) | 7.73 | 6.61 | 8.23 | 7.85 |
| Discarding new entrants into employment | 6.09 | 5.23 | 6.27 | 6.29 |
| Discarding new entrants and within-firm mobility | 4.58 | 3.82 | 4.77 | 4.46 |

| | Time-trend in mobility | | | |
|---|---|---|---|---|
| | Base sample | Base sample + Government | Base Sample + Part-time | Base Sample + Self-employed |
| Total Mobility (Raw series) | 0.0034 | 0.0021 | 0.0050** | 0.0024 |
| Discarding new entrants into employment | 0.0008 | -0.0004 | 0.0012 | -0.0003 |
| Discarding new entrants and within-firm mobility | -0.0016 | -0.0011 | -0.0016 | -0.0038* |

NOTE: "Raw series" are those displayed in figure 4 for the three-digit level only. "Discarding new entrants in employment" indicates that the sample is restricted to those employed in two consecutive years. "Discarding new entrants and within-firm mobility" indicates that the sample is restricted to those employed in two consecutive years and that only occupational switches that are accompanied by a change in employer are considered as genuine. "1980's decade" refers to years 1982 to 1989, "1990's decade" to years 1990 to 1999 and "2000's decade" to years 2000 to 2009. In the bottom panel, results are from linear regressions in which the dependent variable is predicted mobility and the independent variable is the year (divided by 10). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

groups of workers differently. For instance female workers are overrepresented among government and part-time workers. Focusing exclusively on the baseline measurement of occupational switches, figure 5 plots the time series obtained under alternative sample dispositions. While confirming that the baseline results are robust to a disaggregation by gender groups, the figure depicts a slightly different dynamics for male and female workers. Section 6 below analyzes why this does not show in the series of total mobility.

As another sensitivity check, alternative specifications to infer mobility for those previously unemployed were tested. Among the different versions of equation (2) that were experimented, a time trend and additional interaction terms between this time trend and the education dummies were added. I also tested the inclusion of a cubic in age and included the unemployment rate among the independent terms along with the following interaction terms: $unemp * time$, $unemp^2 * time$, $unemp * time^2$, $unemp * age * time$, $unemp * age^2 * time$, $unemp * age^3 * time$, $unemp^2 * age * time$, $unemp^2 * age^2 * time$, $unemp^2 * age^3 * time$. The results were virtually unchanged, which suggests to focus on the parsimonious regression equation (2).




NOTE: Occupational mobility at the three-digit level (fraction of workers in employment). The modified sample refers to the base sample augmented with either government workers (figures on top) or part-time and self-employed workers (figures in the middle) or restricted to workers aged 23 to 55 years old (figures at the bottom).

Figure 5: Occupational Mobility in France, 1982-2009: Different Sample Restrictions

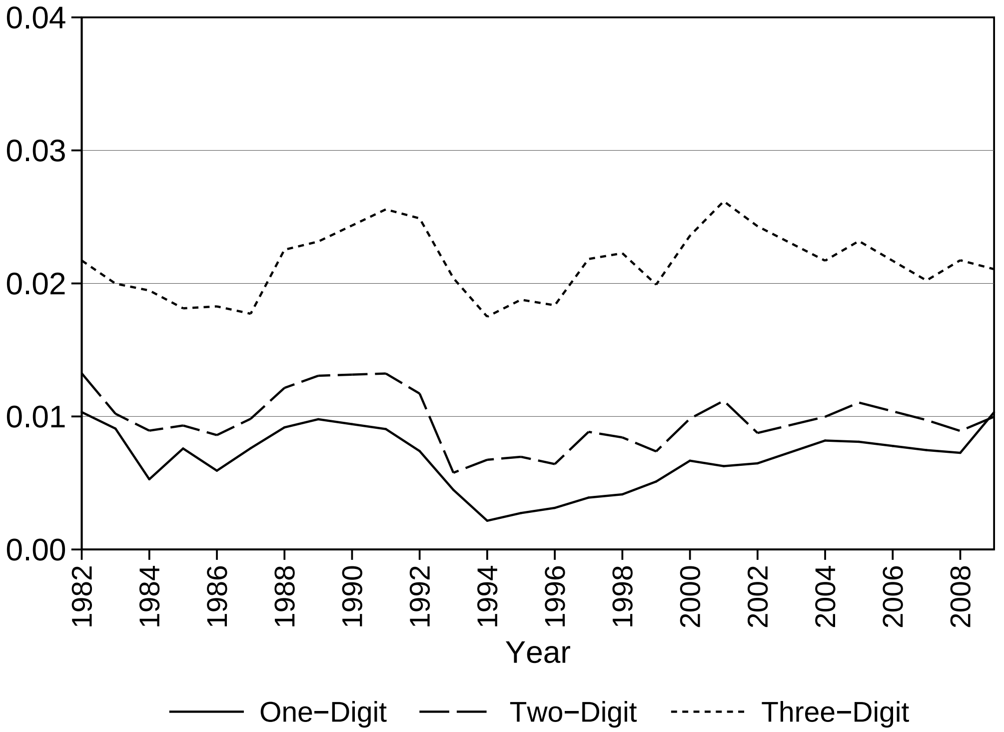
### 5.2. *Net Mobility*

Another important question regarding worker flows across occupations is: are they due primarily to shifts in the demand for labor in different sectors and occupations of the economy, as in Lucas Jr and Prescott (1974)'s island model, or to idiosyncratic uncertainty in individual choice of occupation, as emphasized by Miller (1984) and McCall (1990)? To assess the importance of the former source of mobility, I follow a standard practice in the literature and compute net mobility rates. Net occupational mobility at time $t$ measured over a time-horizon of one year is defined as

$$\text{net}_t = \frac{1}{2}\sum_m |s_{m,t} - s_{m,t-1}| \tag{3}$$

where $s_{m,t}$ is the fraction of workers in occupation $m$ year $t$. This time series measures the reshuffling required to accommodate the reallocation of employment across occupations between two consecutive years, ignoring the moves that cancel out in the aggregate.

To calculate net mobility at the three-digit level, the 2003 update of the occupation classification must be




NOTE: Net occupational mobility at the different digit levels (fraction of workers in employment).

Figure 6: Net Occupational Mobility in France, 1982-2009: Different Digit Levels

taken into account. The new classification contains more occupations which not only mechanically increases net occupational mobility but may also track a larger share of net occupational mobility. Besides there are several empty occupation cells before 2003 whereas there is only one such cell after 2003. This is confirmed by the marked jump of the time series of net mobility in 2003, contrary to the time series for gross worker flows.

To align net mobility after 2003 on the time series obtained with the 1982 occupational classification, I regress net occupational mobility at the three-digit level against a constant, the two-digit series and a dummy that takes the value of one for years 2003 onwards. The coefficient on the dummy variable measures the extent of additional net mobility tracked by the 2003 classification. I subtract this "excess" mobility from the raw series of net mobility for the years following the introduction of the new classification. This "excess" mobility, however, is limited to 0.6 percentage points. A reason why the inconsistencies across periods are limited is the fact that occupations with the largest share of workers before 2003 contain approximately as many individuals as their post-2003 counterparts (around 2.5% of the labor force)[14].

Figure 6 plots the time series of net occupational mobility at the different digit level. Net occupational mobility corrected for the change in occupational classification averages 0.7% at the one-digit level, 1.0% at the two-digit level and 2.1% at the three-digit level. The levels of net mobility are remarkably stable from years to years. Only at the highest level of disaggregation do they exhibit significant yearly variations, similar to that of gross mobility. That is, according to the discussion of the cyclical patterns of gross mobility, net occupational mobility is pro-cyclical. The three-digit level of net mobility also exhibits a small (but statistically insignificant) upward trend over the period under study.

To assess the contribution of idiosyncratic uncertainty with respect to individual choices to total mobility, one can subtract the switches that "do not cancel out" (Jovanovic and Moffitt, 1990) in the aggregate to gross

[14]These occupations are [5421: "Bank-clercs"] and [5631: "Nursery assistants"]. The occupation with the largest share of total employment is [5411: "Secretary"] which contains more than 4% of individuals before 2003.

mobility rates. This new series – occupational churning – averages 3.1% at the one-digit level, 3.8% at the two-digit level and 5.2% at the three-digit level. Thus, at the most disaggregated level of the occupational classification churning accounts for two-thirds of total occupational mobility. Kambourov and Manovskii (2008) and Moscarini and Vella (2003) report a similar figure of two-thirds for occupational churning in the United States. That is, the comparison of gross and net flows suggests that demand shifts and individual choice of occupation play quantitatively similar roles in total mobility in France and in the US, despite the large differences in the levels of gross and net mobility between the two countries.

## 6. Mobility by Groups

### *6.1. Within-Group Levels*

In this section I disaggregate occupational mobility within education and gender groups of the population, and further breaks these groups into age groups. I first analyze the differences in levels between groups and then turn to the trends in mobility within these groups. Table C2 reports the levels of occupational mobility at the different digit level in each age, education and gender cell. I consign the table to AppendixC and summarize the main findings in this subsection.

*Education*

Focusing first on the role of education, table C2 reveals that there are very little differences in the levels of mobility between individuals with different educational background. Even though mobility slightly rises with education, the order of magnitude of the differences across groups is only one percentage point. Kambourov and Manovskii (2008) also report limited differences in mobility across education groups.

Interpreting this limited role of education is complex for a number of reasons. First, it is unclear whether skills acquired at school should be considered as complement or substitutes to the specific skills that workers acquire on the job. Therefore, one cannot predict whether individuals with more skills acquired at school should be less concerned about destroying specific skills upon occupational switches. Second, even with four education groups, each group aggregates a number of education categories which may differ substantially in terms of their true educational content, notably in terms of the importance of vocational education – which is likely to make individuals less mobile. Third, workers may self-select into occupations that serve as "stepping-stones" for other occupations (Jovanovic and Nyarko, 1997) and this cannot be perfectly predicted by their diploma.

*Age*

Turning to the differences across age groups, it is clear that mobility falls with worker's age, regardless of their educational background. Mobility among male individuals for instance averages 15% for workers aged less than 29 years old, 7% for workers aged 30 to 39 years old, 4.4% for workers aged 40 to 49 years old and 2.5% for workers aged more than 49 years old. This is consistent with the occupational-matching and human capital literatures, which both predict more churning among younger workers (see e.g. Miller, 1984 and McCall, 1990). The rest of the empirical literature on occupational mobility also finds similar evidence of declining mobility over the life-cycle: job switches that are more complex in the words of Neal (1999) prevail among younger workers.

The decline of mobility with worker's age is also non-linear, since mobility falls by 50% when workers move from the first age category to the second one, and roughly by 30% from the second to the third and then from the third to the fourth age categories. This is noteworthy, as one might have expected promotions for older workers to result in a less sharper decreasing pattern. Thus, either promotions are scarce or they occur early in the career path of workers. This non-linear decline with worker's age is also consistent with the two literatures aforementioned. For instance Miller (1984) shows that a worker is more likely to try occupations that are more rewarding but also riskier early in his/her career, and then settle into occupations within which he/she has explored most jobs.

*Gender*

Mobility is always higher among male workers. Overall and across education groups, there is a 1 percentage point difference in the levels of occupational mobility for male and female workers. Differences are noticeably higher among younger workers, particularly for workers with lower educational levels. For instance in the first education category (low education), mobility among workers aged less than 29 years-old averages 16% for male and only 11% for female workers. Moscarini and Vella (2003) also report lower rates of occupational mobility among female workers. This calls for investigating whether this gender gap in mobility is specific to switches across occupations or whether this reflect lower mobility of women across jobs in general.

### *6.2. Within-Group Trends*

Using the same age, education and gender cells, table 3 reports the trends in mobility within these groups at the different digit levels. Figures 7 and 8 complement this table with the plots of some of the time series that are the most representative of the within-groups dynamics in mobility over the period considered. In figure 7 male and female workers are pooled together. In figure 8 the different age-groups are pooled together, the sample is restricted to workers aged 23 to 55 years-old and includes part-time workers.

Table 3 reveals that gross occupational mobility increased within several age and education groups, especially for female workers. Figures 7 and 8 further indicate that these increases occurred at a steady pace throughout the period under study. Thus the time trends displayed in table 3 give a relevant picture of the dynamics of occupational mobility within groups.

When looking at the groups within which mobility increased, one notices that the increases are more significant and more pronounced among younger workers, less-educated workers and female workers. On the other hand, even if (almost all) the time-trends are not statistically significant, one notices that mobility at all digit levels decreased among male workers aged more than 30 years old and with medium or higher educational levels. In words that are often used to analyze employment experiences in Europe, occupational mobility increased among labor market "outsiders", both relative to "insiders" and in absolute terms.

A closer look at the less-educated workers in table 3 reveals that the increase in occupational mobility occurred within most age groups in this education category. Moving to the groups of workers with more education, the time-trends in mobility decrease for older workers but they remain positive for younger workers. It is well known that the labor market position of younger and unskilled workers worsened over the past decades. For instance unemployment rates are higher among these workers and they became more likely to work in temporary jobs. Since workers who transit from school to work in the previous year are excluded from the sample, the empirical evidence presented in figure 7 suggest that the employment experiences of younger workers are more chaotic even several years after entering the labor market.

Table 3 unambiguously shows that mobility increased for female workers, regardless of their age and educational background. When these increases are compared to mobility among male workers, one notices that they are steeper for younger and less-educated workers. Given that female workers were initially less mobile than male, what happened over the years 1982 to 2009 is that their mobility rates caught up those of male workers (figure 8), except for the most skilled women whose mobility rates are virtually indistinguishable from those of male workers.

How can this increase in mobility for female workers be interpreted? On the one hand, this might indicate that women's career paths became more similar to those of male workers, which raises a number of questions.

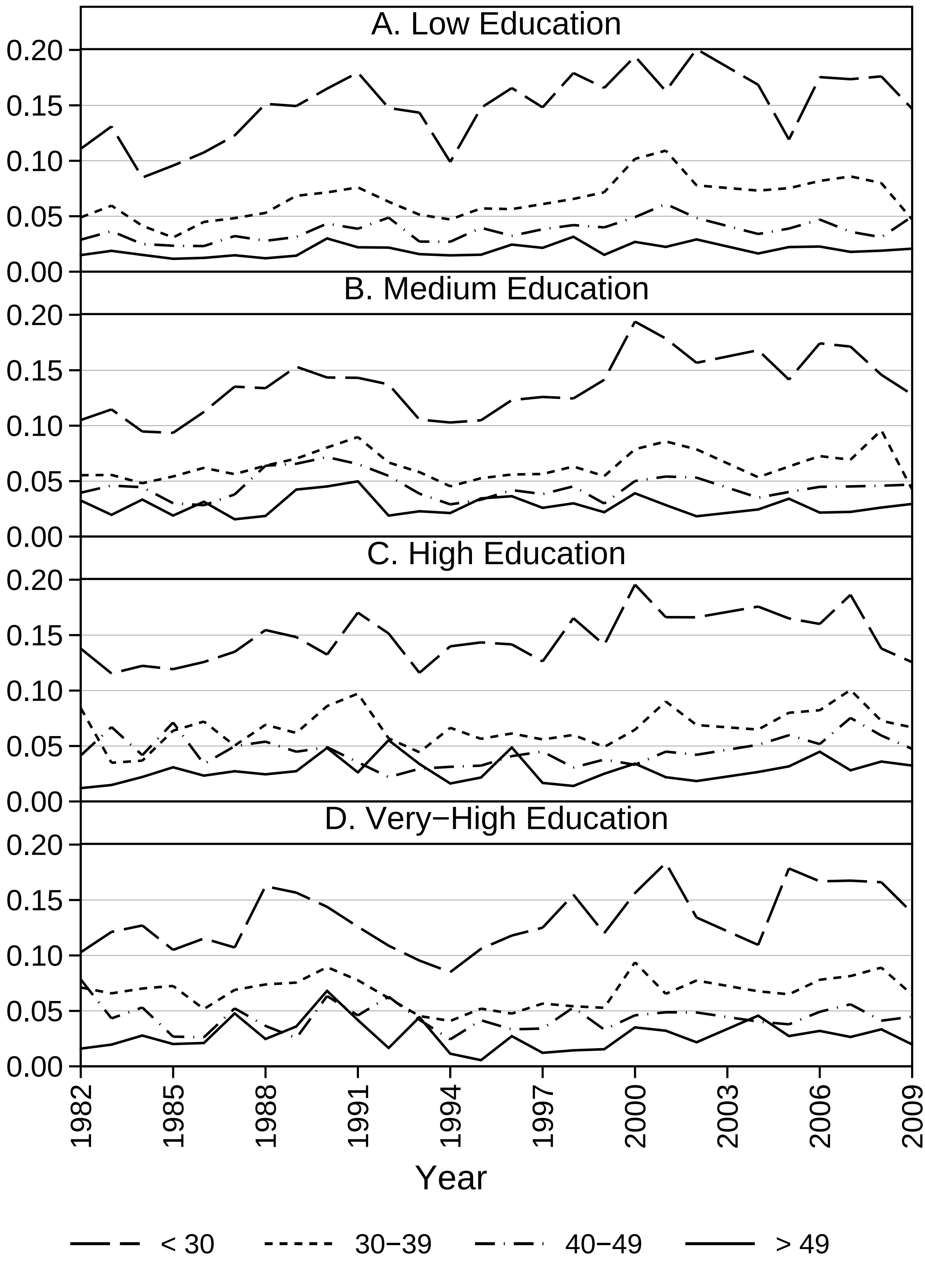
Table 3: Estimated Time-trends of Mobility by Age, Education and Gender, Different Digit Levels

| | Male Workers | | | Female Workers | | |
|---|---|---|---|---|---|---|
| | 1-Digit | 2-Digit | 3-Digit | 1-Digit | 2-Digit | 3-Digit |
| | (1) | (2) | (3) | (1) | (2) | (3) |
| | | | **A. Low Education** | | | |
| Overall | 0.0008 | 0.0011 | 0.0006 | 0.0004 | -0.0019 | 0.0051* |
| less than 29 years old | 0.0148** | 0.0181** | 0.0144* | 0.0174** | 0.0211** | 0.0429*** |
| 30-39 years old | 0.0052* | 0.0071** | 0.0099** | 0.0073** | 0.0092** | 0.0218*** |
| 40-49 years old | 0.0028** | 0.0038* | 0.0053** | 0.0007 | 0.0006 | 0.0083*** |
| more than 49 years old | 0.0003 | 0.0007 | 0.0039** | -0.0001 | -0.0002 | 0.0006 |
| | | | **B. Medium Education** | | | |
| Overall | -0.0051*** | -0.0065*** | -0.0060* | -0.0015 | -0.0027 | -0.0026 |
| less than 29 years old | 0.0101*** | 0.0082** | 0.0154*** | 0.0184*** | 0.0160*** | 0.0278*** |
| 30-39 years old | -0.0011 | 0.0004 | 0.0012 | 0.0057*** | 0.0080*** | 0.0118*** |
| 40-49 years old | -0.0026 | -0.0013 | -0.0012 | -0.0030 | 0.0003 | 0.0011 |
| more than 49 years old | -0.0049** | -0.0018 | -0.0003 | -0.0011 | 0.0022 | -0.0015 |
| | | | **C. High Education** | | | |
| Overall | 0.0006 | 0.0034 | 0.0034 | -0.0039 | 0.0041 | 0.0091** |
| less than 29 years old | -0.0036 | 0.0032 | -0.0005 | 0.0036 | 0.0170*** | 0.0276*** |
| 30-39 years old | 0.0021 | 0.0041 | 0.0049 | 0.0020 | 0.0070*** | 0.0125*** |
| 40-49 years old | -0.0035 | -0.0034 | -0.0013 | 0.0029 | 0.0048* | 0.0140*** |
| more than 49 years old | 0.0018 | 0.0010 | -0.0004 | 0.0028 | 0.0022 | 0.0106*** |
| | | | **D. Very-High Education** | | | |
| Overall | 0.0016 | -0.0002 | 0.0018 | 0.0041 | 0.0076** | 0.0060* |
| less than 29 years old | 0.0105** | 0.0041 | 0.0139* | 0.0126*** | 0.0203*** | 0.0170*** |
| 30-39 years old | -0.0011 | -0.0015 | -0.0019 | 0.0040 | 0.0063* | 0.0116** |
| 40-49 years old | -0.0010 | -0.0006 | 0.0007 | 0.0004 | 0.0005 | -0.0045 |
| more than 49 years old | -0.0008 | -0.0015 | -0.0028 | 0.0048* | 0.0061** | 0.0097** |

NOTE: Results are from linear regressions in which the dependent variable is predicted mobility and the independent variable is the year (divided by 10). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

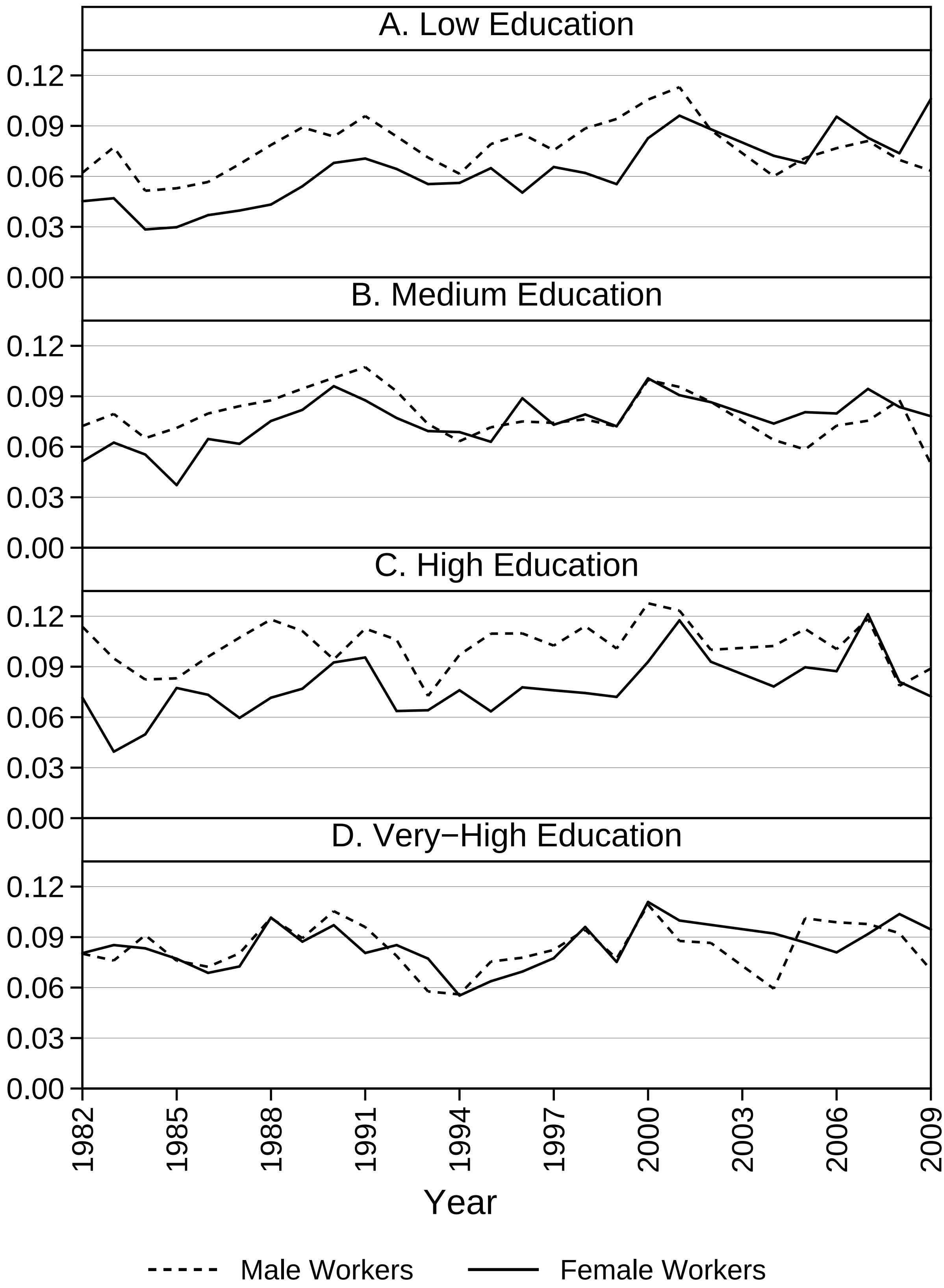
For instance I am not aware of any study documenting a decline in the wage gender gap in France over the 1980s and 1990s. Thus, if career paths became more similar, why did wage inequalities persist? Another possible interpretation is that this indicates more dualism in the French labor market, as for the increases in mobility of young and unskilled male workers. This would be consistent with the burst of short-time jobs among female workers, another indicator of increased dualism (see e.g. Wasmer, 1999).

Overall, what do the time-trends in occupational mobility reported in this subsection suggest regarding disturbances in the French labor market? Given that mobility rates are low in France, all the increases shown in table 3 and figures 7 and 8 were substantial. These increases were also concentrated on some sub-groups of the population. Thus, if one accepts Ljungqvist and Sargent (2008)'s interpretation that upward trends in occupational mobility are evidence of more disturbances in the labor market, then my findings suggest that the French labor market became more turbulent over the past decades but that these turbulences were unequally distributed across workers and were concentrated on the young, the unskilled and on female workers.




NOTE: Occupational mobility at the three-digit level (fraction of workers in employment). The different age and education groups include both male and female workers.

Figure 7: Occupational Mobility in France, 1982-2009: Different Age and Education Groups




NOTE: Occupational mobility at the three-digit level (fraction of workers in employment). Base sample + part-time workers. Younger (less than 23 years-old) and older (more than 55 years-old) are excluded from the calculations.

Figure 8: Occupational Mobility in France, 1982-2009: Different Gender and Education Groups

Table 4: Demographic Change in France, 1982-2009: Summary Statistics

| | Base Sample | | | | Base Sample + Part-Time Workers | | | |
|---|---|---|---|---|---|---|---|---|
| | Mid-1980s | Mid-1990s | Mid-2000s | Change over the period (%) | Mid-1980s | Mid-1990s | Mid-2000s | Change over the period (%) |
| Mean Age (in years) | 35.87 | 37.23 | 41.04 | 9.11 | 36.03 | 37.24 | 41.27 | 9.10 |
| Female Workers (%) | 33.43 | 34.52 | 35.74 | 20.26 | 38.22 | 41.36 | 44.42 | 11.06 |
| Education (%) | | | | | | | | |
| *Low* | 42.26 | 29.13 | 22.70 | -62.62 | 43.25 | 30.24 | 23.90 | -64.38 |
| *High* | 10.06 | 11.81 | 15.47 | 102.20 | 9.90 | 11.85 | 15.54 | 96.57 |
| *Very-High* | 10.01 | 17.79 | 22.91 | 221.63 | 9.81 | 17.21 | 22.19 | 228.50 |

NOTE: "Mid-1980s" refers to years 1984 to 1986, "Mid-1990s" to years 1994 to 1996 and "Mid-2000s" to years 2004 to 2006. The percentage change over the period is calculated by comparing averages over the first three and last three years of the period under study.

## 7. The Role of Composition Effects

### *7.1. Changing Demographics in France*

Why do the positive time-trends reported in table 3 do not show in the time series of aggregate mobility? One candidate to answer this question is the changing composition of the population in employment. This might affect measured mobility through two channels. First, even if mobility remains constant within each subgroup of the population, an increase in the relative size of groups characterized with lower mobility diminishes aggregate mobility. Second, the trend in aggregate mobility remains unchanged if the relative size of groups within which mobility increased shrinks sufficiently rapidly over the period. The goal of this section is to quantify the impact of such effects on measured mobility.

Before describing changes to the composition of employment in France, a third possible channel through which these might affect mobility must be mentioned. While the two channels aforementioned rest on the assumption that within-groups mobility is independent of demographic changes, it is conceivable that mobility within some groups changes in response to shifts in the relative size these groups. However, this is arguably not relevant here. First, as shown below, the bulk of composition effects comes from the aging of the population in employment, which reflect natural aging of the workforce. For instance higher unemployment among younger workers remained roughly unchanged throughout the period. Thus it did not cause the increase in the mean age of the population of employment. Second, the endogeneity of mobility rates to demographic changes is more likely to occur when one focuses on the educational composition of the population rather than its age structure. However, as shown below, education plays no role in the composition effects analyzed here. It is thus accurate to adjust for composition effects, in particular for aging of the population.

I focus on three characteristics of the population in employment: its age, educational level and the share that is female. Table 4 describes changes along these three dimensions to the composition of full-time as well as that of full-time plus part-time employment. Those were substantial. First the mean age of the population of employed persons rose from 35.8 to 41.2 years old. Second, educational attendance increased dramatically: for instance the proportion of workers with no diploma dropped from 46.8% to 16.5% while the fraction of workers who studied more than two years after the baccalaureat rose from 8.6% to 30.3%. Third, female workers increased their participation to the labor market: their share in total employment rose from and 37% to 44.2%, and from 33.1% to 36.1% when the analysis is restricted to full-time employment.

*7.2. Methodology*

There is necessarily some arbitrariness when one intends to measure what would have happened in the absence of composition effects, as one needs to choose a reference period to neutralize composition effects. This subsection develops a methodology that aims at being as insensitive as possible to the choice of the base year that serves to adjust measured mobility rates.

Denoting $\omega_t(g)$ the fraction of workers in group $g$ (where "group" refers to one of the age-education cell studied in section 6) and $\text{mob}_t(g)$ mobility within this group at time $t$, total gross mobility $\text{mob}_t$ at time $t$ is given by

$$\text{mob}_t = \sum_g \omega_t(g)\, \text{mob}_t(g) \tag{4}$$

One possibility to quantify the impact of demographic change on measured occupational mobility is to compute a re-weighted time series that fixes the size of each group $g$ to its value at time $t_0$:

$$\text{mob}_{t,t_0} = \sum_g \omega_{t_0}(g)\, \text{mob}_t(g) \tag{5}$$

The difference $\text{mob}_t - \text{mob}_{t,t_0}$ then gives the changes in observed mobility rates that are caused by changes in the relative size of each sub-group $g$ from $t_0$ to $t$.

A drawback of the method, however, is that changes that are attributed to composition effects might be sensitive to choice of the base year $t_0$. To alleviate this, one can compute a chain-weighted series of changes in total gross mobility that are attributable to composition effects:

$$\Delta_{t,t_0} = \sum_{\tau=t_0}^{t-1} \sum_g \left(\omega_{\tau+1}(g) - \omega_\tau(g)\right) \frac{\text{mob}_\tau(g) + \text{mob}_{\tau+1}(g)}{2} \tag{6}$$

Comparing successive values of this new series is then more relevant since

$$\Delta_{t+1,t_0} - \Delta_{t,t_0} = \sum_g \left(\omega_{t+1}(g) - \omega_t(g)\right) \frac{\text{mob}_t(g) + \text{mob}_{t+1}(g)}{2} \tag{7}$$

does not depend on the choice of $t_0$. That is, the difference between the successive values of the time series $\Delta_{t,t_0}$ reflect changes in the relative sizes of groups weighted by averages of mobility across periods.

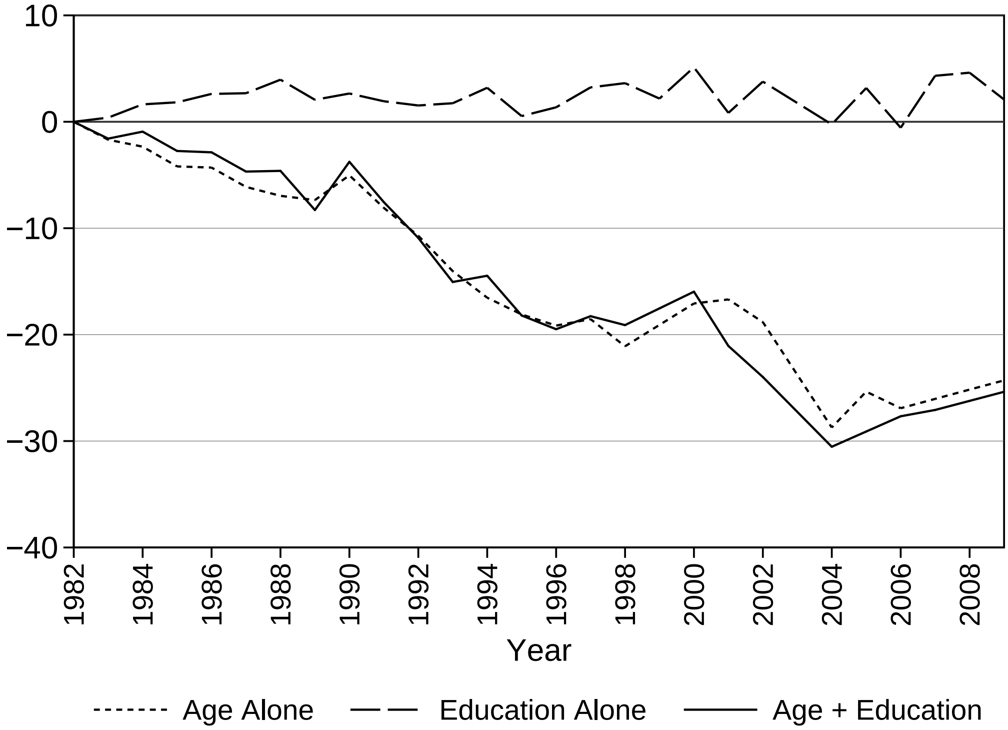
In practice, the quantitative findings based on $\text{mob}_t - \text{mob}_{t,t_0}$ and $\Delta_{t+1,t_0} - \Delta_{t,t_0}$ reveal very similar. The reason for this is that changes in the relative size of age and education groups as well as increases in mobility occurred at a steady pace throughout the period under study. Because the difference $\text{mob}_t - \text{mob}_{t,t_0}$ is more intuitive, I use this measurement to illustrate qualitatively the impact of composition effects. On the other hand, I rely on the difference $\Delta_{t+1,t_0} - \Delta_{t,t_0}$ to quantify these effects.

*7.3. Results*

*The Impact on Gross Mobility*

The main results regarding the impact of composition effects on aggregate mobility rates are shown in figure 9, which reports the difference $\text{mob}_t - \text{mob}_{t,1982}$ expressed as a percentage of $\text{mob}_t$ after choosing 1982 as a reference year. The figure indicates that, by the late 2000s, mobility would have been higher by a factor of 20 to 30 percent had the composition of the population in employment not shifted towards older and more educated workers. The figure also reveals that education *per se* had almost no impact on the measurement of mobility, which is a consequence of the similarity of mobility rates across education groups.

Using a different procedure explained in footnote 15 to re-weight individual observations, figure 1 in the introduction provides a second assessment (and a different graphical depiction) of how composition effects




NOTE: Each line represent $\text{mob}_t - \text{mob}_{t,t_0}$ expressed in percentage of $\text{mob}_t$. The base year $t_0$ is 1982. The calculations are for male and female workers. "Age alone" indicates that the groups considered are the age classes, "Education only" that the groups considered are the education classes and "Age + Education" that the groups considered as the age "times" education classes.

Figure 9: The impact of Composition Effects on Occupational Mobility in France, 1982-2009

affect the time trends in aggregate mobility. Because this procedure allows a more flexible treatment of age and takes into account changes in the share of the population in employment that is female, it attributes a larger role to composition effects: that is, after choosing 1982 as a reference year, taking those into account leads to almost a twofold increase in mobility over the period considered.

As previously noted, the choice of the base year $t_0$ might affect the changes in mobility rates that are imputed to composition effects. For this reason, table 5 reports the difference $\Delta_{t+1,t_0} - \Delta_{t,t_0}$ expressed as a percentage of mobility averaged over each decade. As in figure 9, I analyze the role of age and education separately and then take them into account simultaneously. I also analyze the impact of composition effects separately for male and female workers and then pool them together. Finally, because of the important differences in the share of female workers in full-time and part-time employment, I compare the results in the base sample and in the extended sample comprising both full-time and part-time workers.

Comparing figure 9 with column (5) in table 5, it is clear that the choice of the base year $t_0$ does not quantitatively affect the results in figure 9. For instance composition effects as measured in table 5 diminished measured mobility by a factor of 9 to 14% during the 1990's and 2000's, which does not depend on $t_0$. Thus, the finding that composition effects diminished measured mobility rates by 25% is robust to the method used to assess this impact. It is also robust to the sample restrictions that are adopted (male vs. female workers, full-time vs. part-time workers), as the similarity of columns (1) to (6) shows.

In table 5, the difference between the combination of age and education vs. age alone is larger than in figure 9. This is not due to imprecise estimates of the relative size and mobility rates in each age and education cell since, with a few exceptions in some years, most of these finer age-education cells contain more than 3% of the population. Instead, this is a consequence of the fact that a finer partition of the population mechanically results in higher changes in mobility attributable to composition effects. Meanwhile the differences with figure

9 are tiny and confirm that the bulk of composition effects is due to the aging of the population.

*The Impact on Net Mobility*

With the method described in subsection 7.2, it is not possible to assess the impact of demographic change on net mobility since net mobility is not the weighted average of net mobility within different age and education groups. Yet, given that gross mobility would have increased had the composition of the population in employment not changed throughout the period, it is important to determine whether the same would have occurred for net occupational mobility, thus leaving occupational churning unchanged.

To answer this question, I re-weight *individual* observations to fix the population structure to a base year[15]. These new weights allow me to compute occupational employment shares that are not contaminated by changes in the composition of the population in employment. As in subsection 7.2, the choice of the base year might be a concern. Therefore I repeat the analysis for each year of the period under study. Table 6 reports the results from these calculations for the mid-year in each decade under study. For direct comparison, it also reports gross mobility rates computed with these individual weights.

The impact of changes to the composition of the population in employment are similar for gross and net mobility. That is, using the individual weights to hold the 1985 structure of the population unchanged, I find that both gross and net mobility at the three-digit level increased over the years 1982 to 2009. Besides, the coefficient on the time-trends are similar, which suggests that occupational churning remained unchanged. When I use individual weights for the other years (i.e. 1995 and 2005), the coefficients on the time trends shrink but remain positive and statistically significant for gross mobility, as the last row of the table shows. In sum, after taking composition effects into account, gross mobility increased but there is no evidence of a change in the fraction of switches that are due to worker churning across occupations.

## 8. Conclusion

This paper aimed at documenting a series of key facts regarding occupational mobility in France over the years 1982 to 2009. The findings may serve as an element of appreciation of the French labor market specificities. They may also be compared to the results for the United States, the only country where occupational mobility has been documented along similar lines.

This paper makes two key contributions. First, it establishes time series of occupational mobility within different age, education and gender groups that are consistent over almost three decades. To do so, it overcomes several statistical issues that significantly alter the measurement of occupational mobility, bias its level and generate inconsistencies in the time series. While many studies of occupational mobility limit the analysis to occupational switches that are accompanied by a change in employer, the present paper also identifies within-firm mobility and mobility upon exiting unemployment. Ignoring these movements would result in mobility rates that are about 50% lower than the ones reported here. Second, it documents and quantifies large composition effects that affect aggregate mobility rates. The picture of aggregate occupational mobility in France

[15] The procedure to re-weight individual observations in some year $t_1$ to hold constant the population structure of year $t_0$ is as follows. First I pool the two cross-sections of years $t_1$ and $t_0$ and define an indicator that takes the value of one if the observation is in the cross-section of year $t_1$ and 0 if it is in the cross-section of year $t_0$. Then I run a Logistic regression of this indicator against a cubic polynomial of age freely interacted with educational and gender dummies. The three educational categories are "low education", "high education" and "very-high education" ("medium education" is the omitted group). The model is then used to predict the probability $p_i^*$ that observation $i$ is in the cross-section of year $t_1$. The adjusted weight $\omega_i^*$ is finally obtained as

$$\omega_i^* = \frac{1-p_i^*}{p_i^*}\omega_i$$

where $\omega_i$ is the original weight of individual $i$, i.e. the weight used in the rest of the analysis.

Table 5: The Cumulative Impact of Composition Effects on Occupational Mobility in France, 1982-2009

| | Cumulative impact of demographics on the levels of mobility (%) | | | | | |
|---|---|---|---|---|---|---|
| | Male Workers | | Female Workers | | All Workers | |
| | Base | Base + Part-time | Base | Base + Part-time | Base | Base + Part-time |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Age alone | | | | | | |
| 1980's Decade | -0.90 | -0.75 | -2.63 | -1.79 | -1.38 | -1.04 |
| 1990's Decade | -8.20 | -7.78 | -10.50 | -10.14 | -9.03 | -8.64 |
| 2000's Decade | -8.63 | -7.97 | -10.57 | -10.90 | -9.11 | -9.21 |
| Education alone | | | | | | |
| 1980's Decade | 3.17 | 2.86 | 7.65 | 6.83 | 4.12 | 4.04 |
| 1990's Decade | 1.29 | 0.94 | 3.62 | 1.72 | 1.79 | 1.34 |
| 2000's Decade | 2.45 | 2.10 | 4.18 | 2.60 | 3.03 | 2.33 |
| Age + Education | | | | | | |
| 1980's Decade | -2.09 | -2.12 | 0.53 | 0.66 | -2.15 | -1.68 |
| 1990's Decade | -11.53 | -11.28 | -14.77 | -15.57 | -13.55 | -13.35 |
| 2000's Decade | -14.42 | -14.02 | -14.61 | -17.66 | -14.55 | -16.00 |

NOTE: The table reports $\Delta_{t+9,t_0} - \Delta_{t,t_0}$ expressed as a percentage of mobility averaged over the decade. For instance in rows labeled "1980's decade", the figures indicate the difference $\Delta_{t+9,t_0} - \Delta_{t,t_0}$ divided by the average of mobility over the years 1982 to 1989 (this ratio is then multiplied by 100). "Age alone" indicates that the groups considered are the age classes, "Education only" that the groups considered are the education classes and "Age + Education" that the groups considered as the age times education classes. "1980's decade" refers to years 1982 to 1989, "1990's decade" to years 1990 to 1999 and "2000's decade" to years 2000 to 2009.

Table 6: The Impact of Composition Effects on the Trends in Occupational Mobility, 1982-2009

| | Gross Mobility | | | Net Mobility | | |
|---|---|---|---|---|---|---|
| | 1-Digit | 2-Digit | 3-Digit | 1-Digit | 2-Digit | 3-Digit |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Raw Series | 0.0003 | 0.0002 | 0.0034 | -0.0002 | -0.0005 | 0.0008 |
| Base year: 1985 | 0.0045** | 0.0058** | 0.0096*** | 0.0015* | 0.0014** | 0.0020*** |
| Base year: 1995 | 0.0032** | 0.0046** | 0.0076*** | 0.0010 | 0.0004 | 0.0011* |
| Base year: 2005 | 0.0016 | 0.0031** | 0.0055** | 0.0003 | -0.0006 | 0.0004 |

NOTE: "Raw Series" refer to the series displayed in figures 4 (gross mobility) and 6 (net mobility). In the other rows, "base year" refers to the base year of the reweighting procedure of individual observations described in footnote 15. The time series obtained after implementing this procedure are then regressed on a constant and a time trend (year divided by 10). The table displays the coefficient on the time trend from these different regressions.. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

dramatically changes after taking into account these effects: by the late 2000s mobility would have been higher by 25% relative to what is observed in the raw data.

Together with the similar studies for the United States (Moscarini and Thomsson, 2007 and Kambourov and Manovskii, 2008), the empirical results of the present paper provide researchers with a series of facts characterizing some aspects of the functioning of labor markets on both sides of the Atlantic. With no pretense to be exhaustive, this conclusion underlines the links between these aspects and findings of the empirical literature on occupational mobility.

The lower levels of occupational mobility documented in this paper can be viewed as another example of the much debated lack of worker mobility in Europe. Potential explanations for the lower rates of occupational mobility in France may thus be found in contributions to these debates. For example through their impact on hiring (Pries and Rogerson, 2005) and separation (Ljungqvist, 2002) decisions, labor market policies have been shown to diminish worker turnover, which encompasses worker mobility across occupations. They may also interact negatively with geographic mobility, as discussed by Hassler et al. (2005), and thereby reduce occupational mobility by tying individuals to the occupations concentrated in the location where they reside.

Aside from these correlations between various mobility decisions, there may be reasons why worker mobility in France is particularly lower when it is measured across occupations rather than, say, across employers. For instance, Wasmer (2006) explains that higher firing costs raise the returns to specific human capital and thereby induce workers to invest more into this type of human capital. This may rationalize the lower levels of occupational mobility in France, if the specificity of human capital is better defined at the occupation level (Kambourov and Manovskii, 2009). Occupations are also the relevant unit of analysis for various labor market policies, such as the rules for collective layoffs in France, which may be another reason for higher worker attachment to their occupation of employment.

Turning to the trends in occupational mobility, there are at least two empirical debates that illustrate the importance of measuring worker mobility across occupations consistently over a long period of time.

To date, identifying an increase in economic turbulence in the data has proved elusive. The present paper and the similar studies for the United States show that, contrary to most job and worker flows, the reallocation of workers across occupations became more intense during the past decades. In turn, this raises new questions. For instance, why were these trends previously unnoticed, i.e. why are they compatible with flat job and worker flows? Furthermore, can we interpret the trends in mobility as evidence of an increase in disturbances, as Ljungqvist and Sargent (2008) argue? Or should we interpret them more positively as, for instance, enhanced opportunities for workers to redesign their career paths?

The past decades have also been described as a period of polarization of labor markets. In the United States Autor et al. (2006) show that both tails of the wage distribution have been subjected to important shifts. Similar patterns of polarization are documented by Goos and Manning (2007) in the United Kingdom. On the other hand, no changes of similar magnitude affected the wage structure in France. Yet, the present paper shows that occupational mobility in France increased among more vulnerable workers while mobility of more protected workers remained roughly unchanged. This is consistent with a dualization of the labor market, taking the form of more flexible career paths for labor market "outsiders". An important question for the future is to determine whether a common mechanism is at play behind these changes. Most empirical findings of the present paper may be readily used to calibrate models of worker mobility, and thus to answer these crucial questions.

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## AppendixA. Interviewing Techniques

This appendix describes the survey questions and instructions given to interviewers to implement the dependent coding procedure summarized in figure 2. For the 1982 to 1989 and 1990 to 2002 waves, the previous occupation of employment (*PP* in the language of section 3) is dependently coded for those interviewed for the first time. For the 2003 to 2009 waves, the current occupation of employment (*P* in the language of section 3) is dependently coded for those re-interviewed.

*Dependent Coding in the 1982-1989 and 1990-2002 Surveys*

In the 1982 to 1989 waves of the FLFS, interviewers were instructed to code *PP* with explicit reference to *P*:

*For those employed one year before the interview, ask the whole series of questions describing one's activity and duties even if the individual is employed at the time of the interview and declares upfront that no change has occurred since the previous interview. You are asked to do so in order to record all transitions on the labor market* [FLFS 1982 questionnaire, p.25].

From 1990 to 2002, similar instructions were given to interviewers:

*Has the activities or duties of the respondent changed since March of the previous year, for instance has his/her occupation of employment changed, has he/she been promoted with the same employer or changed employer?* [FLFS 1990 questionnaire, p.10]

Even if the second instructions are less explicit, the previous occupation of employment was always coded after making an explicit reference to the respondent's current occupation. On the other hand, re-interviewed individuals were never asked to compare their current occupation with the one recorded in their previous interview.

*Dependent Coding in the 2003-2009 Surveys*

To minimize non-response in the re-designed FLFS, the occupation of employment of those re-interviewed is coded using dependent interviewing. Specifically, re-interviewed individuals are asked the following questions B1, B2a and B2c:

1. Since last interview, has [your main occupation (Q.B1)] / [your workplace (Q.B2a)] / [your duties (Q.B2b)] changed?
   Yes ⟶ Skip to independent occupation question
   No ⟶ Skip to question 2
2. In the previous interview, you reported that you were (last interview occupation of employment) and that you were working for (company's name). Is this still an accurate description of your current job?
   Yes
   No⟶ Skip to independent occupation question [FLFS 2003 questionnaire, p.10]

On the other hand after 2003, interviewers were no longer given specific instructions regarding the previous occupation of employment of individuals surveyed for the first time. Moreover the length of the questionnaire increased dramatically: in the post-2003 surveys individuals interviewed for the first time are asked to describe their previous occupation of employment only after 50 pages of questionnaire.

## AppendixB. Cleaning Procedure

The cleaning procedure to identify genuine occupational switches at three-digit level relies on two additional indicators to measure transition on the labor market: one for a change in classification of the jobs held in two consecutive years and one for a change in employer. These auxiliary information were obtained as follows:

- In the FLFS both the current job and the job held in the previous year are classified according to some of their technical characteristics. Jobs are classified into 9 categories which convey information that are highly correlated – and sometimes redundant – with occupations: example of these categories include skilled manual laborer, teacher, etc. The classification of jobs used in the FLFS was updated in 1990 and 2003. This is not a concern since changes were very minor. Besides, I do not observe jumps in the mobility of workers across job classifications when I plot this time series against time.
- For changes in employer, I use information about job tenure and consider that workers who report less than 12 months of tenure with the current employer changed employer during the previous year. In addition, in the 2003 to 2009 waves, the FLFS adopted a dependent coding procedure whereby re-interviewed individuals are asked whether they are still working at the same company. This allows me to verify the accuracy of the job tenure variable over a time horizon of a quarter. I noticed no systematic divergences, which confirms that changes in employer can be measured accurately with the job tenure variable.

Making use of these additional indicators, I discard the apparent occupational switches that do not coincide with a change in employer at the one and two-digit levels or with either a change in employer or a change in the classification of the job for occupational switches at the three-digit level. Table B1 reports the results of this cleaning procedure.

Table B1: Impact of the Cleaning Procedure on Measured Mobility Rates

| Period | Sample Size | | 1-Digit (1) | 2-Digit (2) | 3-Digit (3) |
|---|---|---|---|---|---|
| 1982-1989 | 101,686 | Number of occupational switches in the raw data | 3,227 | 4,096 | 6,132 |
| | | Fraction of these apparent switches that are discarded (%) | 25.66 | 22.71 | 15.67 |
| | | Post-correction mobility rate (%) | 2.36 | 3.11 | 5.09 |
| 1990-2002 | 185,539 | Number of occupational switches in the raw data | 5,859 | 7,350 | 14,644 |
| | | Fraction of these apparent switches that are discarded (%) | 25.87 | 22.91 | 35.40 |
| | | Post-correction mobility rate (%) | 2.34 | 3.05 | 5.10 |
| 2003-2009 | 96,987 | Number of occupational switches in the raw data | 2,846 | 3,485 | 9,185 |
| | | Fraction of these apparent switches that are discarded (%) | 38.19 | 35.01 | 51.65 |
| | | Post-correction mobility rate (%) | 1.81 | 2.34 | 4.58 |

NOTE: Columns (1), (2) and (3) read as follows for each sub-period under study. The first row shows the number of occupational movers in the raw data. The second row indicates the fraction of these apparent switches that are turned down by the cleaning procedure. The third row displays the mobility rates obtained after applying the cleaning procedure. This last figure is expressed in percentage of the population employed in two consecutive years.

## AppendixC. Additional Tables

Table C1: Estimation Results for Model (1) at the Different Digit Levels

| | Results for Male Workers | | | Results for Female Workers | | |
|---|---|---|---|---|---|---|
| | 1-Digit | 2-Digit | 3-Digit | 1-Digit | 2-Digit | 3-Digit |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Age | -0.6033 | -0.0062 | 0.0395 | 0.5901 | 0.8659 | -0.0649 |
| | (0.0215) | (0.0220) | (0.0210) | (0.0247) | (0.0258) | (0.0246) |
| AgeSq. | 0.0193 | 0.0035 | 0.0045 | -0.0107 | -0.0153 | 0.0088 |
| | (0.0006) | (0.0006) | (0.0005) | (0.0006) | (0.0007) | (0.0006) |
| Time*Age (*10e2) | 0.0289 | -0.0022 | -0.0041 | -0.0293 | -0.0430 | 0.0028 |
| | (0.0011) | (0.0011) | (0.0010) | (0.0012) | (0.0013) | (0.0012) |
| Time*AgeSq. (*10e4) | -0.0948 | -0.0139 | -0.0197 | 0.0532 | 0.0756 | -0.0435 |
| | (0.0028) | (0.0029) | (0.0027) | (0.0032) | (0.0033) | (0.0032) |
| Educ1 (d) | -0.3597 | -0.6780 | -0.6766 | 0.0040 | 0.5687 | 0.2577 |
| | (0.0092) | (0.0057) | (0.0080) | (0.0144) | (0.0070) | (0.0098) |
| Educ1*Age | 0.4224 | -0.0497 | 0.7879 | -1.5451 | -2.3734 | -0.7692 |
| | (0.0313) | (0.0317) | (0.0297) | (0.0390) | (0.0410) | (0.0397) |
| Educ1*AgeSq. | -0.0155 | -0.0026 | -0.0261 | 0.0400 | 0.0579 | 0.0149 |
| | (0.0008) | (0.0008) | (0.0007) | (0.0010) | (0.0010) | (0.0010) |
| Educ1*Time*Age (*10e2) | -0.0199 | 0.0052 | -0.0373 | 0.0772 | 0.1169 | 0.0380 |
| | (0.0016) | (0.0016) | (0.0015) | (0.0019) | (0.0020) | (0.0020) |
| Educ1*Time*AgeSq. (*10e4) | 0.0758 | 0.0091 | 0.1274 | -0.1999 | -0.2873 | -0.0744 |
| | (0.0038) | (0.0039) | (0.0036) | (0.0048) | (0.0050) | (0.0048) |
| Educ2 (d) | 0.0168 | -0.4497 | -0.4327 | 0.2261 | 0.3192 | 0.3718 |
| | (0.0148) | (0.0111) | (0.0141) | (0.0141) | (0.0122) | (0.0069) |
| Educ2*Age | 1.0241 | -0.5824 | 0.1014 | 0.0683 | -0.3158 | 0.7344 |
| | (0.0482) | (0.0483) | (0.0454) | (0.0498) | (0.0501) | (0.0448) |
| Educ2*AgeSq. | -0.0318 | 0.0101 | -0.0072 | -0.0053 | 0.0016 | -0.0284 |
| | (0.0012) | (0.0012) | (0.0011) | (0.0014) | (0.0014) | (0.0012) |
| Educ2*Time*Age (*10e2) | -0.0511 | 0.0306 | -0.0038 | -0.0039 | 0.0149 | -0.0380 |
| | (0.0024) | (0.0024) | (0.0023) | (0.0025) | (0.0025) | (0.0022) |
| Educ2*Time*AgeSq. (*10e4) | 0.1589 | -0.0527 | 0.0343 | 0.0271 | -0.0071 | 0.1435 |
| | (0.0060) | (0.0060) | (0.0056) | (0.0072) | (0.0071) | (0.0062) |
| Educ3 (d) | 0.6452 | -0.4097 | -0.2793 | 0.5727 | 0.5634 | 0.3434 |
| | (0.0065) | (0.0130) | (0.0162) | (0.0106) | (0.0090) | (0.0090) |
| Educ3*Age | 1.5707 | 0.8175 | -0.9364 | -0.3135 | -1.0411 | 0.8544 |
| | (0.0491) | (0.0494) | (0.0462) | (0.0492) | (0.0512) | (0.0499) |
| Educ3*AgeSq. | -0.0408 | -0.0183 | 0.0211 | 0.0039 | 0.0140 | -0.0284 |
| | (0.0012) | (0.0012) | (0.0012) | (0.0013) | (0.0014) | (0.0013) |
| Educ3*Time*Age (*10e2) | -0.0805 | -0.0393 | 0.0479 | 0.0140 | 0.0503 | -0.0436 |
| | (0.0025) | (0.0025) | (0.0023) | (0.0025) | (0.0026) | (0.0025) |
| Educ3*Time*AgeSq. (*10e4) | 0.2061 | 0.0890 | -0.1071 | -0.0175 | -0.0679 | 0.1429 |
| | (0.0061) | (0.0061) | (0.0058) | (0.0066) | (0.0069) | (0.0066) |
| Predicted probability at mean | 0.4648 | 0.5761 | 0.7122 | 0.3912 | 0.4930 | 0.6687 |
| N | 3,169 | 3,169 | 3,169 | 2,851 | 2,851 | 2,851 |

NOTE: The results are from the estimation of the model to predict mobility for those unemployed one year prior to the interview. Educ1, Educ2 and Educ3 are dummy variables that take the value of one for individuals with low, high and very high levels of education, respectively. Individuals with medium level of education are the reference. In the case of continuous variable the reported coefficient show the change in the probability as a result of a marginal increase of the variable around its mean. In the case of dummy variables the reported coefficient show the change in the probability when the dummy variable switches from 0 to 1. Standard errors in parentheses.

Table C2: Average Estimated Mobility by Age, Education and Gender, Different Digit Levels

| | Male Workers | | | Female Workers | | |
|---|---|---|---|---|---|---|
| | 1-Digit | 2-Digit | 3-Digit | 1-Digit | 2-Digit | 3-Digit |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **A. Low Education** | | | | | | |
| Overall | 0.0351 | 0.0456 | 0.0655 | 0.0246 | 0.0350 | 0.0486 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0001) |
| less than 29 years old | 0.0895 | 0.1165 | 0.1597 | 0.0556 | 0.0948 | 0.1093 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| 30-39 years old | 0.0345 | 0.0458 | 0.0670 | 0.0278 | 0.0354 | 0.0525 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| 40-49 years old | 0.0193 | 0.0248 | 0.0375 | 0.0183 | 0.0218 | 0.0374 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| more than 49 years old | 0.0099 | 0.0117 | 0.0195 | 0.0094 | 0.0114 | 0.0192 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| **B. Medium Education** | | | | | | |
| Overall | 0.0414 | 0.0526 | 0.0769 | 0.0334 | 0.0408 | 0.0665 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0001) |
| less than 29 years old | 0.0803 | 0.1030 | 0.1409 | 0.0618 | 0.0779 | 0.1173 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| 30-39 years old | 0.0343 | 0.0435 | 0.0658 | 0.0306 | 0.0363 | 0.0605 |
| | (0.0000) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| 40-49 years old | 0.0214 | 0.0264 | 0.0452 | 0.0207 | 0.0240 | 0.0444 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| more than 49 years old | 0.0147 | 0.0181 | 0.0299 | 0.0087 | 0.0100 | 0.0228 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| **C. High Education** | | | | | | |
| Overall | 0.0487 | 0.0579 | 0.0949 | 0.0463 | 0.0485 | 0.0819 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| less than 29 years old | 0.0964 | 0.1118 | 0.1655 | 0.0853 | 0.0865 | 0.1386 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| 30-39 years old | 0.0358 | 0.0437 | 0.0801 | 0.0309 | 0.0351 | 0.0579 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| 40-49 years old | 0.0217 | 0.0278 | 0.0532 | 0.0155 | 0.0182 | 0.0423 |
| | (0.0001) | (0.0001) | (0.0002) | (0.0001) | (0.0001) | (0.0002) |
| more than 49 years old | 0.0103 | 0.0124 | 0.0297 | 0.0146 | 0.0140 | 0.0318 |
| | (0.0001) | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) |
| **D. Very-High Education** | | | | | | |
| Overall | 0.0330 | 0.0439 | 0.0777 | 0.0406 | 0.0492 | 0.0862 |
| | (0.0000) | (0.0000) | (0.0001) | (0.0000) | (0.0001) | (0.0001) |
| less than 29 years old | 0.0696 | 0.0852 | 0.1414 | 0.0709 | 0.0843 | 0.1372 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| 30-39 years old | 0.0261 | 0.0385 | 0.0709 | 0.0272 | 0.0353 | 0.0678 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| 40-49 years old | 0.0148 | 0.0227 | 0.0450 | 0.0169 | 0.0195 | 0.0437 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0002) |
| more than 49 years old | 0.0126 | 0.0146 | 0.0280 | 0.0129 | 0.0157 | 0.0270 |
| | (0.0001) | (0.0001) | (0.0002) | (0.0002) | (0.0002) | (0.0002) |

NOTES: The table reports the estimates of average occupational mobility. Standard errors in parentheses.