Job and Wage Mobility: An Analysis of the Dynamics of Employment Durations Using Matched Employee and Employer Data from the U.S. and France

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1. Introduction

The ‡exibility of a labor market is often judged by the extent to which individuals move from employer to employer and the extent to which their real wages ‡uctuate in response to economic conditions. The American labor market is usually described as being highly ‡exible with substantial employment mobility and real wage rates that ‡uctuate more than in most other developed countries. The French labor market, by contrast, is usually thought to be substantially less ‡exible with much more limited employment mobility and considerable real wage stability. In this paper we use matched longitudinal employer-employee data from the State of Washington and France to compare and contrast the employment mobility in these two countries and to examine movements in real wage rates. Not surprisingly we con…rm what many other studies have shown concerning the American market: substantial employment mobility and considerable real wage ‡exibility when there is an employment change. More surprising, however, are our …ndings for France: here also there is substantial employment mobility, although the most mobile groups in France are not the same as those in the United States, and there is very substantial real wage mobility on changes of employer.

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In the next section of this paper we describe our two data sources and the methods we used to create the employment durations, nonemployment durations and the associated wage rate dynamics. In the last section we present our results.

2. Data Description

2.1. Description of the DAS

The "Déclarations Annuelles des Salaires" are a large collection of matched employer-employee information collected by INSEE (Institut National de la Statistique et des Etudes Economiques) and maintained in the Division des Revenus. The data are based on a mandatory employer report of the gross earnings of each employee subject to French payroll taxes. The universe includes all employed persons. Our analysis sample covers all individuals employed in French enterprises who were born in October of even-numbered years, with civil servants excluded. Our extract runs from 1976 through 1987, with 1981 and 1983 excluded because the extracts were not built for those years. The initial data set contained 7,416,422 observations. Each observation corresponds to a unique establishment-individual-year combination. The observation includes an identi…er that corresponds to the employee (called NNI below), an identi…er that corresponds to the establishment (SIRET), the …rst 9 digits of the SIRET correspond to the parent enterprise of the establishment (SIREN). For each observation, we have information on the number of days during the calendar year the individual worked in the establishment, as well as the full-time/part-time/intermittent/at home work-status of the employee. Each observation also includes, in addition to the variables listed above, the sex, month year and place of birth, occupation, total net nominal earnings during the year and annualized gross nominal earnings during the year for the individual, as well as the location and industry of the employing establishment.

2.2. Observation selection, variable creation and missing data imputation

2.2.1. Aggregation of establishments

The creation of the analysis data set involved the selection of desired individuals, the aggregation of establishment-level data to the enterprise level, and the construction of variable of interest from the variable already in the data set. Unlike Abowd-Kramarz-Margolis (1997) who focus on full-time workers, we kept all employees irrespective of their work-status. We then created a single observation for each NNI-year-SIREN combination by aggregating within NNI and year over SIRETs in the same SIREN. The work-status for this observation (NNI-year-SIREN) is full-time only if all NNI-year-SIRET observations for this particular SIREN are full-time. It is part-time if one observation at one establishment is part-time. There were no multiple NNI-year-SIRET observations with a intermittent or at home work-status. We used the occupation, location and industry that corresponded to the establishment at which the individual had worked the largest number of days during the year. This reduced the number of observations to 7,413,805. The aggregation of the number of days worked in the same SIREN across its establishments occasionally yielded observations for which the total number of days worked was greater than 360 (the maximum permitted). In this case, we just truncated days worked at 360. We then calculated an annualized net nominal earnings for the NNI-year-SIREN combination. We eliminated all years of data for individuals who were younger than 15 years old or older than 65 years old at the date of their …rst appearance in the data set (sample reduced to 7,159,409 observations).

2.2.2. Imputation

An observation is identi…ed by a combination of two identi…ers, the …rm' id and the person's id. The SIREN number has an internal structure that allows to check for coding errors. But, the NNI number has no such internal control. Even though 90% of today's DADS …les is sent by the responding …rm using an electronic support (tape or diskette), the situation in the eighties was quite di¤erent. Therefore, INSEE had to enter the data into computers. Entry errors in the NNI occurred (exchange in two digits of the NNI, error in one of the digits,...). This phenomenon is well-known at INSEE but, despite many attempts, no general way of solving this problem was found. As a consequence, some observations have a NNI-year-SIREN combination such that no other observation has the same NNI. As a joint product, some NNI-SIREN combinations have a unique missing year. Consider now the case of a worker with observations in, say, 1978 and 1980 in the same enterprise (SIREN) but no observation for 1979. To be true, this would mean that the worker would be employed until some date in 1978 (depending on the number of days worked, December 31 most likely) and also employed after some date in 1980 (depending on the number of days worked, January 1 most likely) in this …rm but not employed at all during year 1979. This is very improbable. In particular, because there is no layoff-type procedure in France in which workers may be recalled by their firms after some period of unemployment. Suggestions of D. Verger (head of the Division Revenus, in charge of the DADS at the beginning of the nineties) led us to adopt the following solution. Whenever an observation was missing in a given year while the same NNI-SIREN combination exists for the preceding and the following year, we created an observation for the missing year with the same NNI-SIREN combination. (We added 193,148 observations). Earnings are computed as the geometric mean of the preceding and following wages (in real terms). All other variables are taken at their following year value.

Because of the 1982 Census, the 1981 and 1983 DADS data were not available. We used the same principle as the one described above to impute missing observations. Hence, imputation was performed only for those individuals that were present in the same firm in 1980 and 1982 or 1982 and 1984. (We added 759,017 observations in the sample). All variables were imputed as above.

2.2.3. Multiple jobs.

Until now, nothing in our procedure rules out multiple jobs holding. Multiple jobs are difficult to handle in our dataset because we only have information on the number of days worked in each NNI-year-SIREN combination. Hence, we do not know the starting and the ending date of the spell in that year (for all spells that last less than 360 days, the maximum). To be able to build spells of employment for each worker, we only kept those individuals that never had strictly more than three employers in any year. We computed the number of employers any worker had in a year. We kept in our analysis file those workers who had at most three different employers in each year. At this stage, our sample only contains workers who hold at most three simultaneous jobs in a given year. Then, we computed the sum of all days worked in each year. If this number was strictly larger than 720 days for some year, i.e. the worker necessarily had three simultaneous jobs at some point of this year, we deleted the individual from our sample.

We define a job spell as an uninterrupted period of employment for a given NNI in a given SIREN over, possibly, many years.

2.2.4. Beginning and end of job spells

Since workers have at most three job spells in a year, the possible sequence of job spells are limited. This allows us to compute exactly the beginning and the end of a job spell. First, we identified for each individual the starting and the end years of a job spell. Then, we ordered these sequences. The different cases are the following:

- When a job spell starts in year t but ends after December 31 of the same year, we compute the starting date within year t as $(360 - DP_t)/360$ where DP_t denotes the number of days worked in year t.
- The end date within year t of a spell is computed symmetrically if the spell started before year t as $DP_t/360$.
- When a spell starts and ends the same year,and if there is no simultaneous job this year, the spell starts at the beginning of the year (January 1).
- When a worker has multiple spells that all start and end the same year, we assume that the sequence of job spells is organized as follows. As long as the sum of days worked in this year is smaller or equal to 360, the job spells are put in sequence one after the other, the first one starting January 1. Any spell with a number of days worked, $DP_{1;t}$ such that $DP_{1;t} + DP_{k;t} > 360$ where $k = 2; 3$ (the other two potential spells) is also placed January 1. This finishes when the three spells (maximum possible) have been taken care of.
- If a job spell ends in year t but started at some previous date, any other job spell that took place the same year t will start at the end of this spell if the total number of days worked for these two spells is smaller or equal to 360 but starts January 1 otherwise. The third spell, if it exists, is placed after the first of the two spells for which the sum is smaller or equal to 360.
- The symmetric principles apply whenever a spell starts in year t and ends after December 31 for all spells that took place in year t.

At the end of this procedure, whenever a worker held three jobs simultaneously (think of a worker with three spells in a given year that all last 200 days), all his (her) observations were deleted. Altogether, both procedures for finding workers holding three simultaneous jobs or more eliminated 46,441 workers from the sample.[1]

[1] Some characteristics of these workers with three or more multiple jobs are described below.

2.2.5. Creation of non-employment spells and transitions between spells

Knowing the sequence job spells, we are in position of identifying the non-employment spells for each worker. First, what we call in the following a non-employment spell, and is indeed a hole between two employment spells in the data, can be either a period of unemployment, non-participation, sickness, self-employment, or in the government (civil servant). Only those spells of non-employment that lie between two employment spells are considered in our analysis. Hence, retirement or death can never generate a non-employment spell. Accordingly, we define a transition as a change of firm with or without a non-employment spell in between.

2.2.6. Education, labor market experience, and job seniority

The DADS itself does not include the education of the individuals. To obtain the education of our sampled workers, we proceeded exactly the same way as Abowd-Kramarz-Margolis (1996), see their data appendix. Using data from EDP (Echantillon Demographique Permanent), we obtained the highest degree (grouped in eight categories) for a 10% subsample of the DADS individuals. Using this subsample, we have run a multinomial logit regression that gave us the probability that a given individual had a given degree conditional on the birth date (10 categories), the skill-level (5 levels), the region of employment (an indicator function if the worker works in Ile de France). This regression had separate coefficients for men and women. We used the resulting regression to impute education for the remaining 90% of the sample. This procedure gave a probability of obtaining each of the eight possible education levels. Using this probability and Table 14 in CEREQ-DEP-INSEE (1990), which gives, for each education category and sex, the average age at which school was left in 1986, we computed an expected school-leaving age. This age is used to compute the labor market experience for each of our workers.

Individuals fell into two categories with respect to the calculation of job seniority: those for whom the first year of observation was in 1976 with 360 worked days in that year and those that appear in the sample after this date or had less than 360 days of work in 1976. For the first category, we estimated the expected length of the in-progress employment spell by regression analysis using a supplementary survey, the 1978 Enquête sur la Structure des Salaires (ESS, Salary Structure Survey). In this survey, respondent establishments provided information on seniority, occupation, date of birth, industry, and work location for a scientific sample of their employees. Using this information, Abowd, Kramarz, and Margolis (id.) estimated separate regressions for men and women that we use to predict seniority for the in-progress spells in 1976 with 360 days worked (all coefficients are reported in Abowd, Kramarz, and Margolis, id., see in particular the data appendix).

2.2.7. Wages and skill-levels

From the nominal earnings collected for each employment spell and year, we first computed the annualized nominal earnings by dividing this number by the number of days worked and remultiplying by 360. Then, we added all mandatory payroll taxes, using tax rules for each year both for employee and employer shares, to these annualized earnings in order to get the annualized nominal total compensation costs. All nominal values were deflated and expressed in 1980 francs. Finally, as in Abowd, Kramarz, and Margolis (id.), we eliminated observations for which the logarithm of the real annualized total compensation cost was more than five standard deviations away from its predicted value based on a linear regression model of this variable on sex, region, experience, and education (see once more the data appendix in Abowd, Kramarz, and Margolis, id.). The sample reduced to 7,058,841 observations.

The skill-levels are defined as follows:

- Engineers, professionnals, managers, technicians, and foremen;
- Skilled blue collars and clerical workers;
- Unskilled blue collar workers.

The skill-level may change within or between firms and spells of any individual. The following table summarizes the employment spells of the French data.

2.3. Description of the Washington State UI Data

The State of Washington maintains a very complete data for a random sample of 10% of the unemployment insurance eligible work force, replenished about every 5 years. These data have been used by Anderson and Myers (1994) and by Allain (1996) to study characteristics of the unemployment insurance system. The data used in this paper come from two types of administrative records, collected in the context of the Continuous Wage and Benefit History (CWBH) project over the 1984-1993 period. The first type are quarterly wages records for a 10% sample of

Washington States UI-eligible workers. Since coverage of workers is nearly universal except for the self-employed, our sample is close to a representative random sample of all employees in Washington State. Our wage file covers the years 1984 through 1993. In addition to the quarterly wage data, the data also include a firm identifier, as well as the firms 4-digit Standard Industrial Classification code, the firms average monthly employment, total wages, taxable wages and tax rate. The second type of data are UI claims records for any sampled worker who filed for UI over the 1984-1993 period. This data set contains, for each claim filed, the workers identifier, the date the claim was filed, the first pay date and the exhaustion date, the total amount of benefits paid, the reason for work separation, as well as the usual personal characteristics (age, sex, race, schooling). A third type of record, related to the job search activities of the unemployed, also contains personal characteristics.

There are between 700,000 and 1,000,000 yearly observations in the wage files, corresponding to 270,688 unique individuals and between 137,361 unique firms in our analysis sample over the 10 year period. A little over 300,000 valid UI claims were filed in Washington State over our sampling period, originating from approximately 150,000 individuals. We are able to match these two types of record, in order to form quarterly job-match histories.

The Washington State data contain both employer and employee identifiers (the latter in scrambled form), thus permitting direct estimation of models with correlated person and firm heterogeneity. Allain (1996) and Abowd and Allain (1996b) have used these data to decompose UI-eligible layoffs into components related to person effects, firm effects and time-varying personal characteristics as shown in equation (SM1) with defined as the quarterly individual layoff rate.

One important limitation of the Washington UI data is that, while the employer-reported earnings, the employer ID, and the employer's industry are observed for all persons in the 10% sample, other personal characteristics, such as sex, race, age, schooling and initial seniority, are observed only when a person has filed for unemployment insurance benefits. Abowd and Allain (1996) imputed the missing personal characteristics using a two-sample multiple imputation algorithm (Rubin 1976, 1987, 1996). We followed a similar procedure in this paper. The ancillary sample used for the missing data imputation was the CPS outgoing rotation groups from 1984 to 1993. The conditioning variables were quintile in the wage rate distribution, one-digit industry and the interaction of these two variables. Based on a joint probabilty model estimated using the CPS, we imputed (sex, race, age, potential experience)-tuples in the Washington UI data for all persons for whom these variables were missing. The imputations were performed five times with independent draws for the random component each time. Given these imputations, we imputed initial seniority for the employment spell in progress when an individual entered the sample using six CPS samples from 1983-1994 that included information on seniority in the current job as the ancillary estimation sample. Details are presented below and in Allain (1996). The result is an analysis-ready data set consisting of five samples with independently imputed missing values. The standard multiple-imputation formulas can be applied to all statistical analyses of these samples.

2.4. The Expectation Step

Our ancillary data consisted of a 1.8 million observation sample of employed persons from the outgoing rotation group files of the Current Population Survey for the months January 1984 to December 1993. For the "expectation" step of our imputation strategy, we computed, for each individual in the ancillary sample the value of our four missing variables (sex, race, schooling and potential labor market experience) and the values of the conditioning variables, which we completely observe in both samples–namely industry and wage, in five real wage quintiles (based on the distribution of the wage data in the CPS sample), and 10 indicators for 1-digit industry classifications. We estimate joint distribution of all four missing variables simultaneously in order to preserve the correlations among these variables from the ancillary sample of employed persons when we impute in the missing Washington UI data.

Let x_{it} represent the vector of individual characteristics, including time-invariant observable characteristics in this section–sex, race, schooling and potential labor market experience; $`_{it}$ represent the unemployment insurance status of individual i at period t. In the Washington State data, we observe:

$$x_{it} = \begin{cases} x_{it}; \text{ if } `_{is} = 1 \text{ for some } s = B_i; :::; L_i \\ \text{missing, otherwise.} \end{cases}$$

Notice that the potentially missing data, x_{it} can be viewed coming from a discrete multivariate distribution function with four dimensions. Let z_{it} represent the vector of variables that is always observed–wage and industry. The variables z_{it} have been classified into exactly Z unique configurations. Using our ancillary sample, we estimated the empirical joint distribution $\hat{P}(x_{it}|z_{it} = z^*)$ using all observations from the CPS files for which $z_{it} = z^*$. Therefore, for a given wage category and industry, we use all the 4-tuples of sex, race, school and potential experience from the CPS as our estimate of the joint distribution function $F(x|z)$.

2.5. The Imputation Step

The second step of the imputation procedure is to predict values for the missing Washington UI data drawn from the appropriate estimated distribution and to repeat this procedure m times (five, in our case) in order to permit accounting for the uncertainty in the process of imputing the missing values. For each (sex, race, schooling, potential experince)-tuple we draw a random number between 1 and the number of data points in the basis of $\hat{F}(x|z)$ for the appropriate z_{iB_i} of individual i with missing data. For $s = B_i + 1, \ldots, L_i$, we advanced the value of potential experience appropriately and left the imputed sex, race and schooling fixed. This imputation procedure is performed, with independent imputation of the residual component, across all five imputation files. Thus,

$$\hat{x}^m_{iB_i} = \hat{F}^{-1}(u^m_i | z_{iB_i})$$

$$\hat{x}^m_{it} = \begin{cases} \hat{x}^m_{iB_i} & \text{for sex, race and schooling} \\ \hat{x}^m_{iB_i} + (t - B_i) & \text{for potential experience} \end{cases} \quad \text{for } t = B_i + 1, \ldots, L_i$$

for $m = 1, \ldots, 5$ and $u^m_i \sim U(0, 1)$.

2.6. Imputation of Seniority

As in the French data, we do not know the seniority for the first employment spell present in the data. In addition, because the mobility between the State of Washington and other states is not negligible, we do not have confidence that the first observation of an employment spell that occurs during a year in which the sample was not refreshed (1985-1987, 1989-1993) is the beginning of a new employment spell. Thus, for each person in the Washington State data we impute the value of seniority for the period before the first observation for that person in the Washington UI sample. The imputation uses the same procedure we described above except that we did the imputation conditional on $x^m_{iB_i}$ and z_{iB_i}. Thus, letting s_{iB_i} denote the value of seniority at the beginning of the data for individual i. Then, we estimate $\hat{F}(s_{iB_i} | x_{iB_i}, z_{iB_i})$ using all observations from the 6 CPS's between January 1984 and December 1993 that contain data on seniority with the same values of x_{iB_i} and z_{iB_i}. Then,

$$\hat{s}^m_{iB_i} = \hat{F}^{-1}(v^m_i | x^m_{iB_i}, z_{iB_i})$$

$\hat{b}_{it}^{m} = \hat{b}_{iB_i}^{m} + (t - B_i)$ for $t = B_i + 1$ until the first observed change of employer.

where $m = 1; \ldots; 5$ and $v_i^m \sim U(0;1)$ independent of u_i^m.

2.7. Statistical Procedures

Rubin has shown that valid statistical inferences can now be made using all the information available to us. Consistent measures of central tendency (moments and conditional moments) are obtained by averaging estimates of these quantities across the five imputation samples. Measures of variability (variances and standard errors) are computed using the classic decomposition of the unconditional variance into the sum of the expected conditional variance and the variance of the conditional expectation. In our case, the statistics of interest are mostly first and second moments, explicitly computed using information from all five imputed data sets based on the following formulas:

$$\hat{\mu} = \frac{1}{5} \sum_{m=1}^{5} \hat{\mu}^{m}$$

and

$$\widehat{Var}(\hat{\mu}) = \frac{1}{5} \sum_{m=1}^{5} \widehat{Var}(\hat{\mu}^{m}) + \frac{1}{5} \sum_{m=1}^{5} (\hat{\mu}^{m} - \hat{\mu})(\hat{\mu}^{m} - \hat{\mu})'$$

for a vector of moments μ, with similar formulas for the other fixed parameters used in our analysis (e.g. logit coefficients and duration analyses).

The multiple imputation procedure described in this section allows us to apply standard complete-data statistical analysis techniques to the Washington State Continuous Wage and Benefits History data set, by solving its missing value problem. It enables us to draw valid statistical inferences using standard methods (correlation analysis, ordinary least-squares regression), by restoring both sampling variability, and the additional variability due to the presence of missing values, to our sample. Further, the use of a secondary data source spared us an arduous and uncertain modeling task, and permitted us to obtain consistent estimates of all the statistical quantities of interest, without imposing any strong theoretical assumptions on our data.

2.8. Spell data

Using the data on employee identifiers, employer identifiers, quarterly hours of work and quarterly earnings for the employer-employee pair, we created job and nonemployment spells in the manner described here. Secondary jobs were elminated by comparing average quarterly hours over the spells and selecting the spell with highest average quarterly hours. Overlapping spells were corrected in a similar fashion for the overlapping segment. To increase the precision of employment durations in this sample we converted the quarterly observations to weekly durations using the wage and hours information. For employment spells of three or more quarters this was done by calculating the average hours per week for all full quarters and applying this calculation to observed hours in the …rst and last quarters for that spell. All middle quarters were assumed to be full quarters(13 weeks), although the job may be full- or part-time. For spells that were contained in 1 or 2 quarters, average weekly hours were imputed from CPS extracts over the same period using 3-digit industry, state and hourly wages as controls. These weekly hours were then applied to the total hours for the spell and totals weeks were calculated.

3. Results

Tables 1 and 2 describe the structure of the French and American data. The rows in each table indicate the number of years in the sample and the columns indicate the number of employers. For the French data we also show the most con…guration of employer in a second line for each year in the sample. Both the French and American data sets have a large number of persons who appear with a single employer in a single year. In general, the French data imply that there are fewer multiple employer individuals in France than in the US (State of Washington, obviously). There is a comparable distribution of length of time in the sample between the two countries. The French data were limited to three employers per year, so the …rst few lines of Table 1 cannot include individuals with more than 3, 4, etc employers.

Table 3 shows the distribution of the number of employment spells by year of birth. Because the French sample runs from 1976 to 1987 and the American from 1984 to 1993, the dates of birth do not correspond to the same age groups across the two countries (sorry). To compare cohorts, for example, 1936-40 in France should be compared to 1946-50 in the United States. The American sample shows a very stable pattern of number of employers regardless of age except possibly for the youngest group, whereas in the French sample the older workers are much more likely to have had fewer employers.

Table 4 shows the distribution of number of employment spells by educational attainment. For comparison purposes we have shown crude correspondance between the educational categories but it is important to remember that the American coding of education by years completed and the French coding by terminal diploma are not really equivalent. In particular, the distinction between general and technical tracks in the French system has no equivalent in the American coding. In addition, the category "no diploma" does not have an American equivalent. The table shows that the different educational groups in France have similar distributions of number of employers whereas for the American sample the least educated groups are more likely to have had multiple employers and the most educated groups are more likely to have had a single employer.

Table 5 shows an ordered logit analysis of the number of employment spells. The simple effects shown in Tables 3 and 4 are confirmed by the mulitivariate analysis. In addition we note that French men are more likely to have had multiple employment spells than French women but the American men are not more likely than American women to have had multiple employment spells. Better educated men and women in France are more likely to have had multiple employment spells but exactly the opposite holds for the US. In France, both the least and best educated individuals are more likely to have had multiple employment spells whereas in the US the probability of having multiple employment spells decreases monotone in education.

Table 6 shows proportional hazard models for the employment durations. As we found for multiple employment spell probabilities, the effect of age of birth is much more important in France than in the United States. Hazard rates for ending an employment spell are roughly constant as a function of date of birth for the American sample whereas they increase strongly as the date of birth gets closer to the present. The coefficients for age at the beginning of the spell show employment hazard rates increase in age, given date of birth, in France while the reverse holds for the US, at least for younger workers. French males have a slightly higher hazard rate than French women whereas the reverse is true for Americans. The hazard ratios associated with education are very similar between the two countries: more educated workers have longer expected employment spells, indicating that the analysis in the ordered logits may have been affected by censored employment spells as well as industry effects, which were not included there.

We now turn our attention to the number of employers per year or quarter (per natural period of observation in the two data sets). Table 7 shows the distribution of employers per period by date of birth. We have not attempted to convert the quarterly American records to their equivalent annual records; however, we note in Table 7 that a single record per individual per period is by far the most common con…guration. There is a tendancy for younger workers to have more employers in a period. Table 8 shows the distribution of employers per period by educational attainment. There is no obvious pattern between these two variables in France. But, in the US, highly educated workers are more likely than low education workers to hold exactly one job in a given quarter whilethe reverse is true for multiple jobs holding in a single quarter. Table 9 presents the results of an ordered logit analysis of the number of jobs per period. The estimates resemble those presented for the number of job spells (Table 5).

The next set of tables report statistics on the nonemployment spells in our data sets. Table 10 presents the distribution of nonemployment spells by year of birth. First, the proportion of workers which experience no nonemployment spell is larger in France than in the US. Then, as was true for employment spells, there is no obvious relation between year of birth and the number of nonemployment spells in the US while there is a clear monotone relation in France - older workers are more likely to have had no nonemployment spells than younger workers. The reverse relation holds across workers who experienced at least one nonemployment spell. Table 11 shows the distribution of nonemployment spells by educational attainment. Highly educated workers seem to be less likely to experience 3 nonemployment spells or more than lower education groups. The ordered logit analysis on the number of nonemployment spells is reported in Table 12. They con…rm the year of birth pattern mentioned previously. All individuals with a diploma equal or superior to the baccalauréat in France are less likely to have many nonemployment spells. While, in the US, we observe an inverse U-shaped relation between years of education and number on nonemployment spells. Furthermore, French males experience more nonemployment spells than women but the reverse relation is true in the US.

We now turn to results on wage changes. Figures 1 and 2 present (log)-wage changes respectively for France and the US. On each …gure, we plot the distribution of wage changes. First, the distribution is plotted for all transitions involving a change in the employing …rm, and second, for all period-to-period within …rm wage changes. The patterns are very similar in the two countries. Within-…rm wage changes are concentrated around zero while between-…rm transitions induce much larger wage changes. When a worker wants a real wage increase, he (she) really has to change …rm. Table 13 presents the distribution of the percent change in real earnings when the individual change employers by industry of origin. The cut points in the distribution of the percent change in real earnings are respectively the …rst decile, the …rst quartile, the median, the third quartile, and the ninth decile. Notice that the larger number in France than in the US may come from the di¤erent time periods (year vs quarter, annualized earnings vs hourly pay). Table 14 presents the same distribution for workers who changed industries and workers who did not change industry. While, in France, a change in industry is associated to small changes in earnings, the reverse is true in the US (remember that all workers have changed employers). Large earnings changes, either positive or negative come from industry changers in the US. Table 15 gets deeper into the same question by controlling for the existence of an intervening spell of nonemployment between the two employment spells. Finally, Table 16 presents estimation results for wage changes within and between …rms. The within results con…rm what Figures 1 and 2 were showing: very few factors can a¤ect wage growth within a …rm. Wage growth between …rms di¤ers in France and in the US in important respects. For instance, the existence of a nonemployment spell between the two employers has a negative impact on wage change in the US while it has a positive one in France. In France, men tend to have negative wage changes while they have small positive changes in the US. The age and birth cohort e¤ects have important e¤ects on wage changes, even very important (and positive) for workers born in the twenties, thirties, and fourties in France. These e¤ects exist in the US but they are much smaller. Highly educated French workers get large positive wage changes while their American counterparts face negative wage changes. The large wage changes in the US come from changes in industries. While the same industry changes in France do not imply such large wage gains or losses.

Table 1
Structure of the individual French data by years in sample and number of employers
Number of individuals (most common configuration of employers)

Years in sample	Number of employers: 1	2	3	4	5	6	7	8	9	10+	Total	Percent
1	349,348	14,274	2,189								365,811	28.9
	1	11	111									
2	65,019	4,759	12,159	3,324	503	61					128,595	10.2
	2	11	111	1111	11111	111111						
3	39,420	28,391	19,109	8,398	3,040	804	204	29	4		99,399	7.8
	3	12	111	1111	11111	111111	1111111	11111111	111111111			
4	37,076	24,569	16,897	10,513	5,546	2,514	870	318	83	28	98,414	7.8
	4	13	112	1111	11111	111111	1111111	11111111	111111111	1111111111		
5	38,059	26,650	15,299	9,711	5,870	3,258	1,748	781	315	137	100,828	8.0
	5	14	114	1113	11112	111111	1111111	11111111	111111111	1111111111		
6	26,930	19,755	13,032	8,223	5,131	3,186	1,841	1,017	522	409	80,046	6.3
	6	15	114	1114	11114	111112	1111111	11111111	111111111	1111111111		
7	13,582	14,909	10,869	7,421	4,801	3,026	1,839	1,135	638	717	58,937	4.7
	7	61	115	1115	11114	111114	1111114	11111112	111111111	1111111111		
8	13,749	17,664	12,461	7,770	4,867	3,133	1,924	1,203	681	936	64,388	5.1
	8	44	512	3114	11115	111114	1111114	11111114	111111114	1111111111		
9	18,274	18,912	13,063	8,586	5,385	3,245	2,102	1,166	735	1,030	72,498	5.7
	9	54	514	4114	11117	211114	1111115	11112114	111111115	1111111114		
10	82,032	54,099	28,674	14,711	7,728	4,083	2,175	1,248	711	1,051	196,512	15.5
	9	91	911	5114	24113	115112	1111114	11111115	111111115	5111111111		
Total	683,489	265,752	143,752	78,657	42,871	23,310	12,703	6,897	3,689	4,308	1,265,428	100.0
Percent	54.0	21.0	11.4	6.2	3.4	1.8	1.0	0.5	0.3	0.3	100.0	

Table 2
Structure of the Employment Spells in the Washington State UI Data by Years and Number of Employers

Years in Sample	Number of Employers											
	1	2	3	4	5	6	7	8	9	10+	Total	Percent
1	157,750	30,423	10,749	3,876	1,601	646	326	146	85	111	205,713	38.1%
2	17,608	13,567	10,559	7,317	4,524	2,582	1,478	764	470	767	59,636	11.0%
3	9,338	7,344	6,395	5,383	4,299	3,133	2,240	1,644	1,027	2,060	42,863	7.9%
4	6,142	5,313	4,517	4,021	3,416	2,785	2,202	1,769	1,314	3,555	35,034	6.5%
5	4,889	4,126	3,728	3,216	2,780	2,367	1,976	1,618	1,275	4,620	30,595	5.7%
6	5,656	3,859	3,379	2,888	2,381	2,062	1,732	1,479	1,190	4,997	29,623	5.5%
7	2,844	2,931	2,764	2,542	2,138	1,918	1,584	1,352	1,115	4,730	23,918	4.4%
8	2,462	2,594	2,564	2,296	2,034	1,727	1,520	1,216	978	4,449	21,840	4.0%
9	2,836	2,639	2,775	2,457	2,151	1,829	1,594	1,240	982	4,248	22,751	4.2%
10+	19,962	13,590	9,900	6,868	4,779	3,343	2,488	1,808	1,276	4,526	68,540	12.7%
Total	229,487	86,386	57,330	40,864	30,103	22,392	17,140	13,036	9,712	34,063	540,513	100.0%
Percent	42.5%	16.0%	10.6%	7.6%	5.6%	4.1%	3.2%	2.4%	1.8%	6.3%	100.0%	

Table 3
Distribution of the Number of Employment Spells in France and the United States by Year of Birth (Percent of Column).

Number of employment spells	Year of Birth								Margins
	≤1925	1926-1935	1936-1940	1941-1945	1946-1950	1951-1955	1956-1960	≥1961	
France									
1	69.3	48.9	40.2	37.8	34.5	28.6	22.5	28.1	36.5
2	21.7	29.0	29.5	28.9	28.8	27.8	27.7	35.7	29.0
3	5.9	12.4	14.8	15.5	16.2	17.3	19.1	19.2	15.7
4	1.9	5.4	7.4	8.1	9.0	10.6	12.7	9.4	8.6
5 or more	1.2	4.4	8.1	9.7	11.5	15.7	18.0	7.6	10.2
United States									
1	25.6	26.5	25.6	24.4	22.8	21.6	20.0	18.0	21.2
2	21.6	21.7	21.4	20.6	20.1	19.0	18.1	16.5	18.7
3	13.7	14.2	13.7	13.4	13.6	13.2	12.7	12.2	12.9
4	9.7	9.8	9.8	10.2	10.3	10.2	10.1	9.8	10.0
5 or more	29.6	27.8	29.6	31.4	33.2	36.2	39.0	43.6	37.3

Sources: France, DAS, sample: 916,080 individuals who appear for more than one year, 1976-88. United States, Washington UI, sample: 422,342 individuals who appear for more than one quarter 1984-93.

Table 4
Distribution of the Number of Employment Spells in France and the United States by Educational Attainment (Percent of Column).

Number of Employment spells	Education (Degree level for France, Years completed for United States)								
	France								
	No Diploma	CEP	BEPC	BAC	CAP BEP	BAC Pro	BTS Dip. Univ.	Etudes Sup	Margins
1	37.2	42.3	37.2	32.4	34.0	38.0	30.5	32.1	36.7
2	28.9	28.2	27.1	28.6	28.5	26.9	35.5	30.1	28.7
3	15.4	13.9	16.8	16.8	16.7	16.7	17.1	18.4	15.8
4	8.1	7.3	9.1	10.1	9.4	8.4	8.9	10.6	8.6
5 or more	10.4	8.3	11.8	12.1	11.4	10.0	8.0	8.8	10.2
	United States								
		8 Years	9-11 Years	Exactly 12 years		13-15 Years	Exactly 16 Years	17+ Years	Margins
1		19.7	17.5	19.5		21.7	28.5	29.7	21.2
2		18.1	16.9	17.9		18.7	21.2	24.3	18.7
3		12.7	12.5	13.0		13.1	13.1	13.4	12.9
4		9.4	9.6	10.3		10.2	9.8	9.1	10.0
5 or more		40.2	43.6	39.4		36.3	27.4	23.6	37.3

Sources: France, DAS, sample: 87,761 individuals with known education appearing for more than one year, 1976-88. United States, Washington UI sample: 422,322 individuals appearing for more than one quarter, 1984-93.

Table 5
Ordered Logit Analysis of the Number of Employment Spells
For France and the United States

	France			*United States*		
	All	Male	Female	All	Male	Female
	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
Independent Variable	(St.Err.)	(St.Err.)	(St.Err.)	(St.Err.)	(St.Err.)	(St.Err.)
Male	0.2023			0.0035		
	(0.0132)			(0.0056)		
White	not used	not used	not used	-0.1168	-0.2027	-0.0067
				(0.0079)	(0.0107)	(0.0117)
Born 1925 or earlier	-1.6219	-1.7267	-1.4439	-0.2394	-0.2494	-0.2192
	(0.0313)	(0.0407)	(0.0500)	(0.0174)	(0.0233)	(0.0263)
Born 1925-1934	-0.7336	-0.8287	-0.5771	-0.2827	-0.3264	-0.2204
	(0.0242)	(0.0316)	(0.0384)	(0.0127)	(0.0172)	(0.0187)
Born 1935-1939	-0.2926	-0.3200	-0.2501	-0.2060	-0.2394	-0.1669
	(0.0258)	(0.0330)	(0.0416)	(0.0140)	(0.0193)	(0.0205)
Born 1940-1944	-0.1623	-0.2018	-0.0954	-0.1065	-0.1513	-0.0579
	(0.0273)	(0.0349)	(0.0440)	(0.0129)	(0.0178)	(0.0186)
Born 1945-1949	ref	ref	ref	ref	ref	ref
Born 1950-1954	0.3121	0.3680	0.2418	0.0892	0.1016	0.0737
	(0.0231)	(0.0306)	(0.0353)	(0.0114)	(0.0156)	(0.0168)
Born 1955-1959	0.5889	0.6170	0.5637	0.1757	0.2166	0.1229
	(0.0218)	(0.0290)	(0.0334)	(0.0111)	(0.0152)	(0.0162)
Born 1960 or later	0.0209	-0.0343	0.0878	0.2704	0.3147	0.2142
	(0.0249)	(0.0333)	(0.0380)	(0.0098)	(0.0136)	(0.0143)
No known diploma	0.2172	0.2767	0.1872	not used	not used	not used
	(0.0455)	(0.0577)	(0.0761)			
CEP (FR) 1-8 years (US)	0.0520	0.1671	-0.0219	0.0485	0.0609	0.0126
	(0.0567)	(0.0775)	(0.0882)	(0.0107)	(0.0134)	(0.0183)
BEPC (FR) 9-11 years (US)	0.1925	0.1423	0.2284	0.1003	0.0863	0.1166
	(0.0756)	(0.1045)	(0.1142)	(0.0088)	(0.0118)	(0.0132)
BAC (FR) 12 years (US)	0.1965	0.2466	0.2428	ref	ref	ref
	(0.0867)	(0.1142)	(0.1369)			
CAP BEP Vocational-Technical (FR)	ref	ref	ref	not used	not used	not used
Bac Professional (FR) 13-15 years (US)	-0.0536	-0.1625	0.2965	-0.1414	-0.1458	-0.1287
	(0.0882)	(0.1114)	(0.1495)	(0.0075)	(0.0105)	(0.0107)
BTS Dip. Univ. (FR) 16 years (US)	-0.0583	-0.1826	0.0143	-0.4931	-0.5473	-0.4089
	(0.0762)	(0.1235)	(0.1039)	(0.0099)	(0.0135)	(0.0000)
Etudes sup. (FR) 17+ years (US)	0.2470	0.2612	0.5766	-0.5588	-0.5920	-0.4927
	(0.0855)	(0.0982)	(0.1895)	(0.0118)	(0.0155)	(0.0183)
Cut point 1-2	-0.5111	-0.6767	-0.5115	-1.4495	-1.5124	-1.3705
	(0.0352)	(0.0396)	(0.0596)	(0.0121)	(0.0162)	(0.0171)
Cut point 2-3	0.7771	0.5570	0.8534	-0.5322	-0.5978	-0.4487
	(0.0353)	(0.0395)	(0.0597)	(0.0119)	(0.0159)	(0.0168)
Cut point 3-4	1.6378	1.3899	1.7607	0.0025	-0.0700	0.0950
	(0.0357)	(0.0400)	(0.0603)	(0.0118)	(0.0159)	(0.0167)
Cut point 4-5+	2.3544	2.0799	2.5280	0.4214	0.3386	0.5271
	(0.0364)	(0.0409)	(0.0616)	(0.0119)	(0.0159)	(0.0168)
Observations	91,590	53,347	38,243	422,342	230,078	192,264
-2 x Log likelihood	258,694	151,555	106,862	1,258,871	-340,219	577,896

Sources: France, DAS, random 1/10 sample of all individuals appearing for more than one year; US, Washington UI, sample: all individuals appearing for more than one quarter. Ordered logit estimated by ML; categories are 1, 2, 3, 4, and 5 or more employment spells.

Table 6
Proportional Hazards Models for Employment Duration in France and the United States

	France		*United States*	
Independend Variable	Coefficient (Std.Err)	Hazard Ratio (Std.Err)	Coefficient (Std.Err)	Hazard Ratio (Std.Err)
Number of previous job spells	0.0131	1.0132	0.0201	1.0203
	(0.0021)	(0.0021)	(0.0002)	(0.0002)
Male	0.0493	1.0506	-0.0218	0.9784
	(0.0050)	(0.0052)	(0.0019)	(0.0019)
White	not used	not used	-0.0505	0.9507
			(0.0025)	(0.0024)
Born 1925 or earlier	-4.5724	0.0103	0.0028	1.0028
	(0.0235)	(0.0002)	(0.0140)	(0.0140)
Born 1925-1934	-3.1287	0.0438	0.0396	1.0403
	(0.0164)	(0.0007)	(0.0080)	(0.0083)
Born 1935-1939	-1.7301	0.1773	0.0353	1.0359
	(0.0123)	(0.0022)	(0.0061)	(0.0064)
Born 1940-1944	-0.8563	0.4247	0.0180	1.0181
	(0.0108)	(0.0046)	(0.0048)	(0.0049)
Born 1945-1949	ref	ref	ref	ref
Born 1950-1954	0.8170	2.2638	-0.0488	0.9524
	(0.0091)	(0.0206)	(0.0042)	(0.0040)
Born 1955-1959	1.5339	4.6360	-0.1133	0.8929
	(0.0108)	(0.0501)	(0.0049)	(0.0044)
Born 1960 or later	2.5392	12.6693	-0.1473	0.8630
	(0.0148)	(0.1875)	(0.0068)	(0.0059)
No known diploma	0.3903	1.4774	not used	not used
	(0.0160)	(0.0236)		
CEP (FR) 1-8 years (US)	-0.0187	0.9814	0.1964	1.2170
	(0.0215)	(0.0211)	(0.0035)	(0.0043)
BEPC (FR) 9-11 years (US)	0.0487	1.0499	0.1148	1.1216
	(0.0283)	(0.0297)	(0.0027)	(0.0030)
BAC (FR) 12 years (US)	0.0755	1.0784		ref
	(0.0308)	(0.0332)		
CAP BEP Vocational-Technical (FR)	ref	ref	not used	not used
Bac Professional (FR) 13-15 years (US)	-0.2061	0.8138	-0.0398	0.9610
	(0.0344)	(0.0280)	(0.0024)	(0.0024)
BTS Dip. Univ. (FR) 16 years (US)	-0.2494	0.7793	-0.1592	0.8528
	(0.0290)	(0.0226)	(0.0036)	(0.0031)
Etudes sup. (FR) 17+ years (US)	-0.2561	0.7740	-0.2109	0.8099
	(0.0329)	(0.0255)	(0.0047)	(0.0038)
Age at the beginning of the spell	0.1120	1.1185	-0.0573	0.9443
	(0.0017)	(0.0019)	(0.0007)	(0.0006)
Age at beginning squared	0.0005	1.0005	0.0005	1.0005
	(0.00002)	(0.00002)	(0.00001)	(0.00001)
Transport & telecomunication (FR)	ref	ref	ref	ref
Transportation and public utilities (US)				
Farm and food industries (FR)	0.2362	1.2664	1.0627	2.8941
Agriculture (US)	(0.0161)	(0.0204)	(0.0056)	(0.0161)
Energy production (FR)	-0.3083	0.7347	not used	not used
	(0.0252)	(0.0185)		
Intermediary goods	-0.0100	0.9901	not used	not used
	(0.0140)	(0.0138)		
Equipment goods (FR)	-0.0894	0.9145	-0.2742	0.7602
Durable manufacturing (US)	(0.0138)	(0.0126)	(0.0053)	(0.0040)
Current consumption goods (FR)	0.1181	1.1253	0.2098	1.2334
Nondurable manufacturing (US)	(0.0137)	(0.0154)	(0.0047)	(0.0059)
Construction (FR)	0.3393	1.4039	0.6653	1.9452
Mining and Construction (US)	(0.0131)	(0.0183)	(0.0044)	(0.0085)
Retail and wholesale trade (FR/US)	0.3407	1.4059	0.3683	1.4453
	(0.0125)	(0.0176)	(0.0036)	(0.0052)
Commercial services (FR)	0.4935	1.6381	0.5788	1.7840
Business services (US)	(0.0119)	(0.0195)	(0.0040)	(0.0072)
Real Estate and Leasing (FR)	0.3357	1.3989	not used	not used
	(0.0267)	(0.0374)		
Insurance carriers and sale (FR)	0.0148	1.0149	not used	not used
	(0.0273)	(0.0277)		
Banks and financial institutions (FR)	-0.2037	0.8157	-0.0237	0.9766
Finance, insurance and real estate (US)	(0.0224)	(0.0183)	(0.0055)	(0.0054)
Non commercial services	0.3304	1.3916	0.0690	1.0714
Health, social and professional services (US)	(0.0149)	(0.0207)	(0.0041)	(0.0044)
Public administration (US)	not used	not used	0.0239	1.0242
			(0.0061)	(0.0063)
Year at the start of spell	yes	yes	yes	yes
Observations	254,706		1,457,883	
censored	37,372		212,207	
-2 x log Likelihood	4,878,524		29,002,636	

Sources: France, DAS, sample random (1/10) of NNI-SIREN observations. US, Wash UI, sample all individuals. Proportional hazards model estimated by maximum likelihood.

Table 7
Distribution of the Number of Jobs (Unique Employers IDs) Per Period in France and the United States by Year of Birth (Percent of Column).

Number of unique employer IDs per period	Year of Birth								Margins
	≤1925	1926-1935	1936-1940	1941-1945	1946-1950	1951-1955	1956-1960	≥1961	
France									
1	95.1	93.9	92.2	91.4	90.6	88.7	86.0	82.8	89.9
2	4.6	5.6	7.0	7.7	8.3	9.7	11.8	14.4	8.8
3	0.3	0.5	0.8	0.9	1.1	1.6	2.2	2.8	1.3
United States									
1	90.4	91.5	91.1	90.6	89.9	89.1	88.0	84.0	88.1
2	8.2	7.3	7.6	7.9	8.5	9.2	10.0	13.2	10.0
3 or more	1.4	1.2	1.3	1.4	1.6	1.8	2.0	2.8	1.9

Sources: France, DAS, sample: 5,844,535 observations, all NNI-years. United States, Washington UI, sample: 7,599,167 observations, all SSN-quarters.

Table 8
Distribution of the Number of Jobs (Unique Employers IDs) Per Period in France and the United States by Educational Attainment (Percent of Column).

Number of unique employer IDs per period	Education (Degree level for France, Years completed for United States)								
	France								
	No Diploma	CEP	BEPC	BAC	CAP BEP	BAC Pro	BTS Dip. Univ.	Etudes Sup	Margins
1	89.7	91.9	90.1	88.4	90.2	90.7	90.2	87.8	90.3
2	8.9	7.2	8.6	10.3	8.5	8.3	9.0	11.4	8.5
3	1.4	0.9	1.3	1.3	1.3	1.0	0.9	0.8	1.2
	United States								
		8 Years	9-11 Years	Exactly 12 years		13-15 Years	Exactly 16 Years	17+ Years	Margins
1		81.8	85.4	88.0		88.5	91.2	92.0	88.1
2		13.0	12.2	10.2		9.8	7.6	6.8	10.0
3 or more		5.2	2.4	1.8		1.7	1.3	1.2	1.9

Sources: France, DAS, sample: 584,421 observations, all NNI-years. United States, Washington UI, sample: 7,599,167 observations, all SSN-quarters.

Table 9
Ordered Logit Analysis of the Number of Jobs (Unique Employer IDs) Per Period
For France and the United States

Independent Variable	*France* All Coefficient (St.Err.)	*France* Male Coefficient (St.Err.)	*France* Female Coefficient (St.Err.)	*United States* All Coefficient (St.Err.)	*United States* Male Coefficient (St.Err.)	*United States* Female Coefficient (St.Err.)
Male	0.1627			-0.0206		
	(0.0098)			(0.0072)		
White	not used	not used	not used	-0.2134	-0.2973	-0.1039
				(0.0097)	(0.0128)	(0.0148)
Born 1925 or earlier	-0.9313	-1.0669	-0.7013	-0.1787	-0.2475	-0.1013
	(0.0277)	(0.0351)	(0.0455)	(0.0240)	(0.0327)	(0.0355)
Born 1925-1934	-0.5486	-0.6512	-0.3593	-0.3505	-0.4983	-0.1792
	(0.0185)	(0.0232)	(0.0311)	(0.0175)	(0.0244)	(0.0251)
Born 1935-1939	-0.2607	-0.3138	-0.1568	-0.2531	-0.3139	-0.1956
	(0.0188)	(0.0230)	(0.0328)	(0.0194)	(0.0272)	(0.0277)
Born 1940-1944	-0.1183	-0.1369	-0.0859	-0.1065	-0.1626	-0.0515
	(0.0195)	(0.0237)	(0.0345)	(0.0169)	(0.0236)	(0.0243)
Born 1945-1949	ref	ref	ref	ref	ref	ref
Born 1950-1954	0.2097	0.2421	0.1650	0.0301	0.0014	0.0556
	(0.0156)	(0.0194)	(0.0260)	(0.0145)	(0.0199)	(0.0211)
Born 1955-1959	0.4899	0.4665	0.5367	0.1353	0.1366	0.1235
	(0.0150)	(0.0191)	(0.0246)	(0.0139)	(0.0191)	(0.0204)
Born 1960 or later	0.8910	0.8568	0.9454	0.3981	0.4106	0.3706
	(0.0192)	(0.0248)	(0.0308)	(0.0125)	(0.0172)	(0.0181)
No known diploma	0.2812	0.3357	0.2593	not used	not used	not used
	(0.0325)	(0.0325)	(0.0400)			
CEP (FR) 1-8 years (US)	0.0869	0.1874	0.0539	0.5369	0.6398	0.3335
	(0.0421)	(0.0421)	(0.0544)	(0.0136)	(0.0167)	(0.0241)
BEPC (FR) 9-11 years (US)	0.1687	0.1966	0.1564	0.1239	0.1222	0.1277
	(0.0559)	(0.0559)	(0.0763)	(0.0110)	(0.0145)	(0.0167)
BAC (FR) 12 years (US)	0.4595	0.3957	0.5795	ref	ref	ref
	(0.0588)	(0.0588)	(0.0785)			
CAP BEP Vocational-Technical (FR)	ref	ref	ref	not used	not used	not used
Bac Professional (FR) 13-15 years (US)	0.1727	0.1099	0.3361	-0.0699	-0.0664	-0.0662
	(0.0604)	(0.0768)	(0.1020)	(0.0095)	(0.0133)	(0.0137)
BTS Dip. Univ. (FR) 16 years (US)	-0.0859	0.0056	-0.1448	-0.2936	-0.3198	-0.2463
	(0.0580)	(0.0909)	(0.0813)	(0.0136)	(0.0190)	(0.0195)
Etudes sup. (FR) 17+ years (US)	0.4655	0.3822	1.0939	-0.2825	-0.3704	-0.1515
	(0.0600)	(0.0693)	(0.1281)	(0.0163)	(0.0224)	(0.0240)
Cut point 1-2	2.6238	2.4909	2.6387	1.9975	1.9119	2.1265
	(0.0288)	(0.0324)	(0.0506)	(0.0194)	(0.0259)	(0.0283)
Cut point 2-3	4.7739	4.6179	4.8308	3.9541	3.7922	4.1872
	(0.0307)	(0.0350)	(0.0537)	(0.0208)	(0.0276)	(0.0308)
Year effects	yes	yes	yes	yes	yes	yes
Observations	584,331	354,208	230,123	768,869	422,851	346,018
-2 x Log likelihood	415,135	257,757	157,118	639,728	353,422	286,157

Sources: France, DAS, random 1/10 sample of all individuals appearing for more than one year; US, Washington UI, sample: 1/10 of all individuals appearing for more than one quarter. Ordered logit estimated by ML; categories are 1, 2, 3 or more unique employer IDs (limit of 3 for France).

Table 10
Distribution of the Number of Nonemployment Spells in France and the United States by Year of Birth (Percent of Column).

Number of non-employment spells	Year of Birth								Margins
	≤1925	1926-1935	1936-1940	1941-1945	1946-1950	1951-1955	1956-1960	≥1961	
France									
0	86.7	72.0	67.2	65.3	62.1	57.0	50.1	63.4	63.6
1	10.8	19.9	20.9	21.0	22.0	22.3	23.9	24.3	21.4
2	1.9	5.6	7.4	8.3	9.4	11.3	14.2	9.1	9.1
3 or more	0.6	2.5	4.5	5.4	6.5	9.4	11.8	3.2	5.9
United States									
0	54.2	56.4	56.4	55.5	54.4	53.4	52.7	52.1	53.5
1	22.5	22.9	22.7	22.9	23.1	22.7	22.5	21.2	22.2
2	11.2	10.4	10.5	11.0	11.4	11.9	12.0	12.4	11.8
3 or more	12.1	10.3	10.4	10.6	11.0	12.0	12.9	14.3	12.5

Sources: France, DAS 1,265,428 observations. Sample: All individuals, 1976-88. United States, Washington UI 518,957 observations. Sample: All individuals, 1984-93.

Table 11
Distribution of the Number of Nonemployment Spells in France and the United States by Educational Attainment (Percent of Column).

Number of non-employment spells	Education (Degree level for France, Years completed for United States)								
	France								
	No Diploma	CEP	BEPC	BAC	CAP BEP	BAC Pro	BTS Dip. Univ.	Etudes Sup	Margins
0	58.3	59.4	52.5	51.6	50.6	55.7	49.1	55.4	55.4
1	24.3	24.8	25.6	27.3	28.1	26.2	34.7	29.0	26.2
2	10.1	9.5	12.9	12.8	12.6	11.4	11.3	11.2	11.0
3 or more	7.2	6.4	9.0	8.3	8.7	6.7	4.9	4.5	7.4
	United States								
		8 Years	9-11 Years	Exactly 12 years		13-15 Years	Exactly 16 Years	17+ Years	Margins
0		56.6	49.7	51.8		54.3	59.4	57.2	53.5
1		19.7	21.1	22.5		22.4	22.3	25.3	22.2
2		10.6	12.8	12.4		11.8	9.8	9.7	11.8
3 or more		13.1	16.5	13.3		11.4	8.5	7.7	12.5

Sources: France, DAS 1,265,428 observations. Sample: All individuals, 1976-88. United States, Washington UI 518,957 observations. Sample: All individuals, 1984-93.

Table 12
Ordered Logit Analysis of the Number of Nonemployment Gaps For France and the United States

Independent Variable	*France* Coefficient (St.Err.)	*United States* Coefficient (St.Err.)
Male	0.0558	-0.0615
	(0.0040)	(0.0053)
White	not used	-0.0894
		(0.0074)
Born 1925 or earlier	-1.5195	-0.0033
	(0.0110)	(0.0170)
Born 1925-1934	-0.5740	-0.1112
	(0.0076)	(0.0124)
Born 1935-1939	-0.2969	-0.1039
	(0.0079)	(0.0137)
Born 1940-1944	-0.1813	-0.0588
	(0.0084)	(0.0126)
Born 1945-1949	ref	ref
Born 1950-1954	0.2703	0.0472
	(0.0068)	(0.0110)
Born 1955-1959	0.5295	0.0743
	(0.0065)	(0.0107)
Born 1960 or later	-0.1887	0.0771
	0.00754	(0.0094)
No known diploma	0.1172	not used
	(0.0147)	
CEP (FR) 1-8 years (US)	0.0420	-0.1406
	(0.0190)	(0.0100)
BEPC (FR) 9-11 years (US)	-0.0490	0.1185
	(0.0259)	(0.0081)
BAC (FR) 12 years (US)	-0.4436	ref
	(0.0292)	
CAP BEP Vocational-Technical (FR)	ref	not used
Bac Professional (FR) 13-15 years (US)	-0.3058	-0.1196
	(0.0299)	(0.0072)
BTS Dip. Univ. (FR) 16 years (US)	-0.1209	-0.3364
	(0.0244)	(0.0097)
Etudes sup. (FR) 17+ years (US)	-0.1867	-0.2580
	(0.0278)	(0.0117)
Cut point 0-1	0.4516	-0.0128
	(0.0113)	(0.0113)
Cut point 1-2	1.6774	0.9881
	(0.0114)	(0.0114)
Cut point 2-3+	2.7297	1.7983
	(0.0118)	(0.0117)
Observations	1,265,428	518,957
-2 x Log likelihood	2,471,080.7	1,221,620.30

Sources: France, DAS, sample: all individuals; US, Washington UI, sample: all individuals. Ordered logit estimated by ML; categories are 0, 1, 2, 3 or more nonemployment spells.

Table 13
Distribution of the Percentage Change in Real Earnings When an Individual Changes Employers in France and the United States by Industry of Origin (Row and Column Percentages)

				France			
Real annualized earnings rate of change	<-60%	-60%< and <-25%	-25%< and <0%	0%< and <35%	35%< and <160%	<160%	Margin
Margin	10.0	15.1	22.6	26.6	15.6	10.1	100
Farm and food industries	3.8 11.0	4.0 17.5	3.6 23.6	3.3 25.6	3.3 14.9	2.5 7.4	3.5 100
Energy production	0.5 10.0	0.4 10.7	0.5 20.8	0.9 42.8	0.4 10.1	0.3 5.6	0.6 100
Intermediary goods	5.7 8.4	6.9 15.6	8.6 28.8	7.8 30.8	5.0 11.5	3.3 4.9	6.7 100
Equipment goods	6.2 8.9	7.5 16.3	8.3 26.8	8.2 31.2	5.3 11.8	3.5 5.0	7.0 100
Current consumption goods	8.1 10.6	8.4 16.7	8.0 23.6	7.7 26.7	6.8 14.0	6.4 8.4	7.6 100
Construction	8.1 7.0	10.7 13.9	12.6 24.5	13.0 29.7	13.8 18.5	7.4 6.4	11.6 100
Retail and wholesale trade	17.2 10.3	17.3 15.7	16.4 22.2	16.0 25.5	17.4 16.3	16.6 10.0	16.7 100
Transport and telecomunication	3.5 9.8	3.8 16.1	3.8 24.2	3.5 26.7	3.3 14.5	3.1 8.7	3.5 100
Commercial services	39.1 10.9	34.9 14.6	32.6 20.5	33.1 24.4	38.0 16.5	47.0 13.1	36.0 100
Real Estate and Leasing	0.7 8.9	0.7 13.2	0.8 22.9	1.0 32.6	0.7 13.6	0.7 8.8	0.8 100
Insurance carriers and sale	0.7 9.0	0.8 14.3	0.8 23.1	1.0 34.3	0.7 12.7	0.5 6.6	0.8 100
Banks and financial institutions	1.3 12.5	1.1 15.7	0.9 20.6	1.1 28.4	0.9 14.5	0.8 8.3	1.0 100
Non commercial services	5.1 12.4	3.5 12.7	3.1 16.8	3.4 22.0	4.5 16.8	7.9 19.3	4.1 100
				United States			
Real hourly wage rate of change	<-37%	-37% < and <-13%	-13% < and <4%	4% < and < 26%	26% < and < 69%	> 69%	Margin
Margin	10.0	15.0	25.0	25.0	15.0	10.0	100
Agriculture, forestry, fishing	9.8 10.8	10.7 17.7	8.3 23.0	8.0 22.0	9.5 15.6	9.9 10.9	9.1 100
Mining and construction	13.0 13.6	10.9 17.1	10.5 27.5	8.7 22.9	7.6 11.9	6.7 7.0	9.5 100
Nondurable manufacturing	8.3 12.6	8.2 18.7	6.7 25.2	6.2 23.6	5.3 12.1	5.2 7.9	6.6 100
Durable manufacturing	6.8 15.1	5.6 18.8	4.3 24.1	4.0 22.1	3.6 12.2	3.5 7.7	4.5 100
Transportation and public utilities	6.3 16.9	4.4 17.6	3.3 22.2	3.3 22.2	3.2 12.6	3.2 8.5	3.7 100
Wholesale and retail trade	21.1 6.6	27.2 12.7	33.1 25.8	34.0 26.5	36.9 17.2	36.0 11.2	32.1 100
Finance, insurance and real estate	5.5 13.8	4.5 16.7	4.1 25.5	3.5 22.0	3.3 12.5	3.8 9.5	4.0 100
Business services	9.9 7.5	12.1 13.7	12.7 24.0	13.8 26.0	15.2 17.2	15.3 11.6	13.3 100
Health, social and professional services	15.8 11.2	14.0 14.9	14.3 25.3	14.5 25.7	12.7 13.5	13.3 9.4	14.1 100
Public administration	3.5 11.4	2.5 12.1	2.6 21.5	3.9 31.6	2.7 13.1	3.1 10.1	3.1 100

Sources: France, DAS, sample 1,103,786 observations, transitions from one firm to another with or without intervening nonemployment. US, Wash UI, sample 1002750 observations transitions from one firm to another with or without intervening nonemployment. Rate of change defined as 100 x (First pay rate at new firm - last pay rate at old firm)/(last pay rate at old firm).

Table 14
Distribution of the Percentage Change in Real Earnings When an Individual Changes Employers in France and the United States by Whether The Industry Changed (Row and Column Percentages)

	France						
Real annualized earnings rate of change	<-60%	-60%< and <-25%	-25%< and <0%	0%< and <35%	35%< and <160%	<160%	Margin
Margin	10.0	15.1	22.6	26.6	15.6	10.1	100
No change in industry	70.6	69.3	66.8	67.0	73.7	75.1	69.5
	10.2	15.1	21.7	25.6	16.5	10.9	100
Change in industry	29.4	30.7	33.2	33.0	26.3	24.9	30.5
	9.7	15.2	24.6	28.8	13.5	8.2	100
	United States						
Real hourly wage rate of change	<-37%	-37% < and <-13%	-13% < and <4%	4% < and < 26%	26% < and < 69%	> 69%	Margin
Margin	10.0	15.0	25.0	25.0	15.0	10.0	100
No change in industry	28.0	31.2	50.5	47.8	30.4	24.5	39.1
	7.2	12.0	32.3	30.6	11.7	6.3	100
Change in industry	72.0	68.8	49.5	52.2	69.6	75.5	60.9
	11.8	16.9	20.3	21.4	17.1	12.4	100

Sources: France, DAS, sample 1,103,786 observations, transitions from one firm to another with or without intervening nonemployment. US, Wash UI, sample 1002750 observations transitions from one firm to another with or without intervening nonemployment. Rate of change defined as 100 x (First pay rate at new firm - last pay rate at old firm)/(last pay rate at old firm).

Table 15

Distribution of the Percentage Change in Real Earnings When an Individual Changes Employers in France and the United States by Whether the Industry Changed and Whether There Was an Intervening Spell of Nonemployment (Row and Column Percentages)

				France			
Real annualized earnings rate of change	<-60%	-60%< and <-25%	-25%< and <0%	0%< and <35%	35%< and <160%	<160%	Margin
No intervening spell of nonemployment							
Margin	9.7	15.2	24.6	28.8	13.5	8.2	100
No change in industry	44.1	46.8	59.6	63.4	49.9	45.7	54.8
	7.8	13	26.8	33.3	12.2	6.9	100
Change in industry	55.9	53.2	40.4	36.7	50.1	54.3	45.2
	12	17.9	22	23.3	14.9	9.9	100
With an intervening spell of nonemployment							
Margin	10.2	15.1	21.7	25.6	16.5	10.9	100
No change in industry	39.6	42.7	52.5	55.4	43.7	41	47.8
	8.4	13.5	23.9	29.8	15.1	9.3	100
Change in industry	60.4	57.3	47.5	44.6	56.3	59	52.2
	11.8	16.5	19.7	21.9	17.8	12.3	100
				United States			
Real hourly wage rate of change	<-37%	-37% < and <-13%	-13% < and <4%	4% < and < 26%	26% < and < 69%	> 69%	Margin
No intervening spell of nonemployment							
Margin	8.6	15.9	30.0	25.2	13.3	6.9	100
No change in industry	29.0	33.8	50.3	42.7	28.7	24.3	39.2
	6.4	13.7	38.4	27.5	9.7	4.3	100
Change in industry	71.0	66.2	49.7	57.3	71.3	75.7	60.8
	10.1	17.3	24.6	23.8	15.6	8.6	100
With an intervening spell of nonemployment							
Margin	10.4	14.7	23.5	24.9	15.5	10.9	100
No change in industry	108.7	91.2	128.4	158.3	117.2	125.7	126.7
	7.4	11.4	30.4	31.6	12.3	6.9	100
Change in industry	282.1	209.2	125.3	162.0	262.6	386.6	197.8
	12.3	16.8	19.0	20.7	17.6	13.5	100

Sources: France, DAS, sample 1,103,786 observations, transitions from one firm to another with or without intervening nonemployment. US, Wash UI, sample 1002750 observations transitions from one firm to another with or without intervening nonemployment. Rate of change defined as 100 x (First pay rate at new firm - last pay rate at old firm)/(last pay rate at old firm).

Table 16
Regression Models for the Change in Log Wage Rates in France and the United States

	France		*United States*	
Independent Variable	Between Firms Coefficient (Std.Err)	Within Firm Coefficient (Std.Err)	Between Firms Coefficient (Std.Err)	Within Firm Coefficient (Std.Err)
Male	-0.0538	0.0067	0.0076	-0.0020
	(0.0069)	(0.0012)	(0.0012)	(0.0003)
White	not used	not used	-0.0046	-0.0001
			(0.0015)	(0.0004)
Lives in Paris	0.0509	0.0047	not used	not used
	(0.0067)	(0.0013)		
Intermittent worker	-0.4087	not used	not used	not used
	(0.0111)			
Part-time worker	-0.5796	not used	not used	not used
	(0.0088)			
Full-time worker	ref	not used	not used	not used
Nonemployment spell at the transition	0.0340	not used	-0.0269	not used
	(0.0075)		(0.0016)	
Duration of nonemployment spell	0.0193	not used	0.0015	not used
	(0.0024)		(0.0000)	
Born 1925 or earlier	0.1763	-0.0251	0.0200	0.0006
	(0.0559)	(0.0033)	(0.0089)	(0.0020)
Born 1925-1934	0.1163	-0.0158	0.0077	0.0010
	(0.0350)	(0.0023)	(0.0051)	(0.0012)
Born 1935-1939	0.0573	-0.0112	0.0071	0.0005
	(0.0227)	(0.0022)	(0.0038)	(0.0008)
Born 1940-1944	0.0457	-0.0012	0.0029	0.0005
	(0.0168)	(0.0022)	(0.0029)	(0.0006)
Born 1945-1949	ref	ref	ref	ref
Born 1950-1954	-0.0180	0.0043	0.0023	-0.0011
	(0.0142)	(0.0019)	(0.0025)	(0.0006)
Born 1955-1959	0.0070	0.0090	0.0026	-0.0020
	(0.0209)	(0.0021)	(0.0030)	(0.0007)
Born 1960 or later	0.0102	0.0159	0.0051	-0.0010
	(0.0310)	(0.0032)	(0.0041)	(0.0011)
No known diploma	0.0811	-0.0078	not used	not used
	(0.0220)	(0.0038)		
CEP (FR) 1-8 years (US)	0.0926	0.0022	0.0168	0.0029
	(0.0286)	(0.0045)	(0.0021)	(0.0006)
BEPC (FR) 9-11 years (US)	0.0397	0.0038	0.0078	0.0000
	(0.0387)	(0.0065)	(0.0016)	(0.0005)
BAC (FR) 12 years (US)	0.0807	0.0148	ref	ref
	(0.0406)	(0.0073)		
CAP BEP Vocational-Technical (FR)	ref	ref	not used	not used
Bac Professional (FR) 13-15 years (US)	0.0518	-0.0046	-0.0090	0.0005
	(0.0433)	(0.0067)	(0.0015)	(0.0003)
BTS Dip. Univ. (FR) 16 years (US)	0.0581	-0.0028	-0.0207	-0.0007
	(0.0387)	(0.0064)	(0.0022)	(0.0004)
Etudes sup. (FR) 17+ years (US)	0.1107	0.0001	-0.0460	-0.0002
	(0.0443)	(0.0070)	(0.0029)	(0.0005)

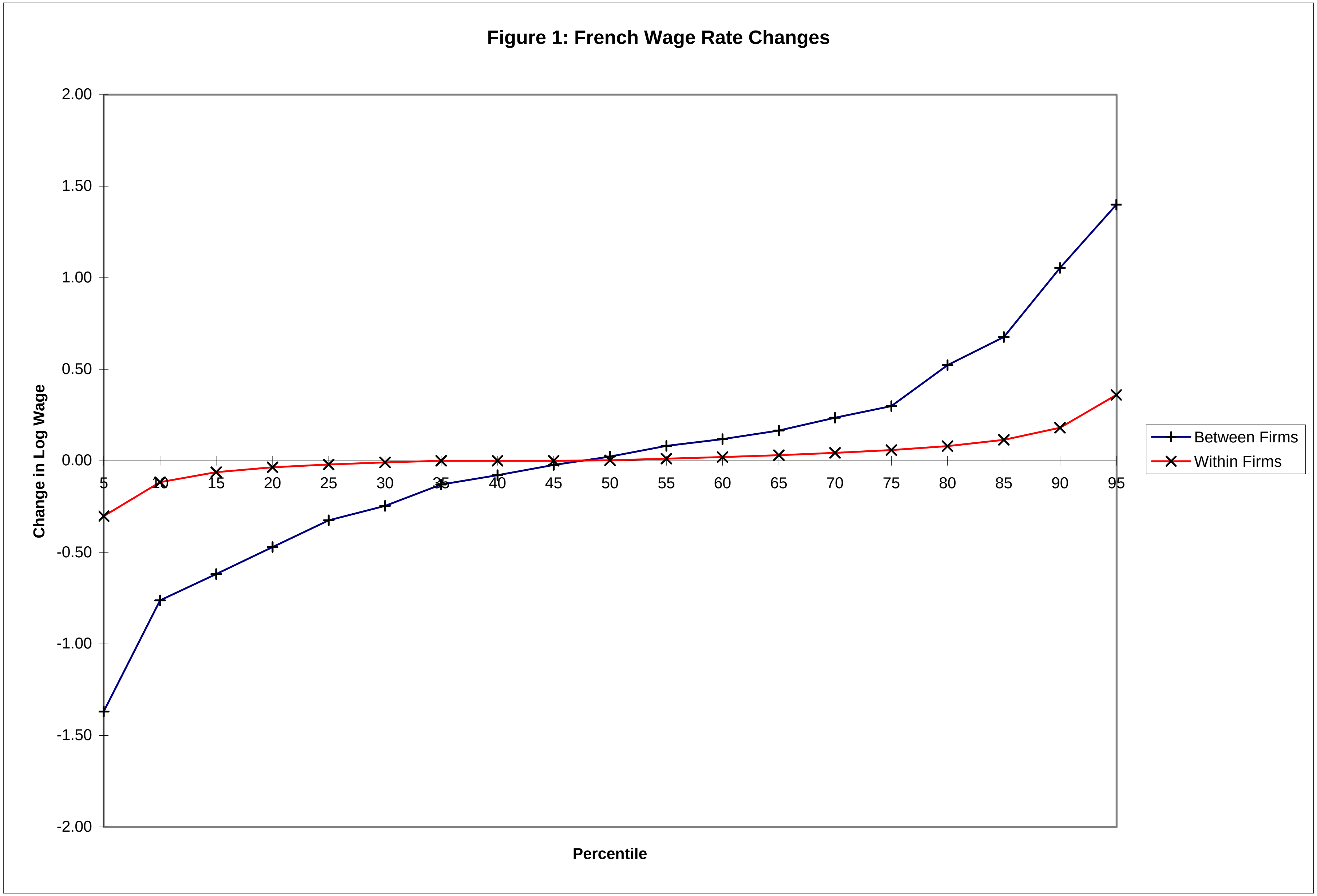
Figure 1: French Wage Rate Changes
2.00
1.50
1.00
0.50
0.00
-0.50
-1.00
-1.50
-2.00
Change in Log Wage
5
10
15
20
25
30
35
40
45
50
55
60
65
70
75
80
85
90
95
Percentile
Between Firms
Within Firms

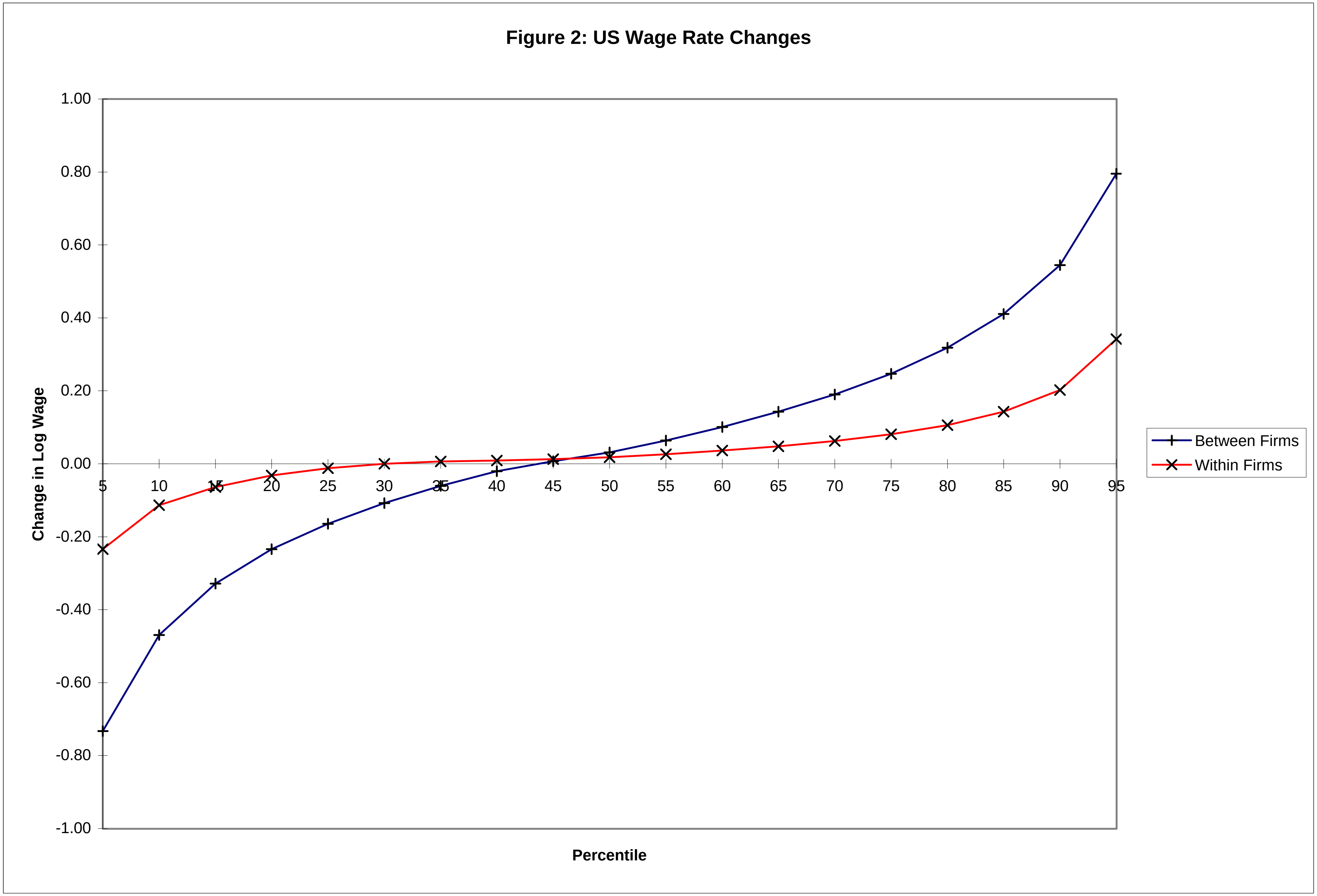

Figure 2: US Wage Rate Changes
1.00
0.80
0.60
0.40
0.20
0.00
-0.20
-0.40
-0.60
-0.80
-1.00
Change in Log Wage
5
10
15
20
25
30
35
40
45
50
55
60
65
70
75
80
85
90
95
Percentile
Between Firms
Within Firms

Table 16 (continued)
Proportional Hazards Models for Employment Duration in France and the United States

	France		*United States*	
	Between Firms	Within Firm	Between Firms	Within Firm
	Coefficient	Coefficient	Coefficient	Coefficient
Independent Variable	(Std.Err)	(Std.Err)	(Std.Err)	(Std.Err)
Age at the beginning of the spell	-0.0051	-0.0004	-0.0040	-0.0013
	(0.0037)	(0.0004)	(0.0004)	(0.0001)
Age at beginning squared	-0.00004	0.00001	0.00003	0.00001
	(0.00004)	(0.00035)	(0.00001)	(0.00000)
Transport & telecomunication (FR)	ref	ref	ref	ref
Transportation and public utilities (US)				
Farm and food industries (FR)	0.0423	0.0156	0.0841	0.0125
Agriculture (US)	(0.0225)	(0.0032)	(0.0034)	(0.0010)
Energy production (FR)	0.0703	0.0070	not used	not used
	(0.0372)	(0.0044)		
Intermediate goods	-0.0191	0.0156	not used	not used
	(0.0192)	(0.0022)		
Equipment goods (FR)	-0.0098	0.0198	0.0051	0.0037
Durable manufacturing (US)	(0.0189)	(0.0021)	(0.0032)	(0.0009)
Current consumption goods (FR)	-0.0533	0.0177	0.0317	0.0044
Nondurable manufacturing (US)	(0.0188)	(0.0022)	(0.0028)	(0.0009)
Construction (FR)	-0.0137	0.0099	0.0218	0.0017
Mining and Construction (US)	(0.0177)	(0.0022)	(0.0026)	(0.0010)
Retail and wholesale trade (FR/US)	-0.0307	0.0191	0.1533	0.0055
	(0.0169)	(0.0019)	(0.0022)	(0.0009)
Commercial services (FR)	-0.0046	0.0122	0.1479	0.0080
Business services (US)	(0.0160)	(0.0018)	(0.0024)	(0.0009)
Real estate and leasing (FR)	-0.0204	-0.0005	not used	not used
	(0.0397)	(0.0074)		
Insurance carriers and sale (FR)	-0.0335	0.0187	not used	not used
	(0.0351)	(0.0058)		
Banks and financial institutions (FR)	0.0617	0.0133	0.0410	0.0106
Finance, insurance and real estate (US)	(0.0334)	(0.0036)	(0.0034)	(0.0010)
Noncommercial services	-0.0701	0.0162	0.0829	0.0044
Health, social and professional services (US)	(0.0206)	(0.0029)	(0.0025)	(0.0009)
Public administration (US)	not used	not used	0.0961	0.0030
			(0.0037)	(0.0010)
Intercept	0.2583	0.0055	0.0952	0.0745
	(0.0884)	(0.0066)	(0.0106)	(0.0031)
Year at the start of spell	yes	yes	yes	yes
Observations	110,241	548,873	1,002,750	5,421,498
R^2	0.0497	0.0018	0.0314	0.0007

Sources: France, DAS, sample random (1/10) of NNI-SIREN observations. US, Washington UI, sample all individuals.