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Changes in the French Wage Distribution 1976-2004 : Inequalities within and between Education and Experience Groups*

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Abstract

This paper studies changes in wage differentials accross education groups for full-time male workers in the French private sector, from 1976 to 2004. We apply quantile regressions to Mincer-type equations to disentangle between- and within-education group wage inequalities, and we describe separately their evolutions. We use a yearly dataset of employer-employee administrative data matched with Census.

Our main results are: (1) the overall wage inequality was stable from 1976 to 1992 and slightly decreased from 1995 to 2004. (2) Within-education group wage inequalities increase with education and are higher across non-vocational degrees than vocational ones. (3) Between-education group wage inequalities increase with experience. (4) The within-education group wage inequalities were rather stable from 1976 to 1992 and decreased between 1995 and 2004, strongly for low levels of experience. (5) The between-education group wage inequalities decreased all over the period, due to decreasing education premiums, particularly for low levels of experience. These results are related to the dramatic evolutions of the French labor market during this period: older cohorts gradually replaced by more educated ones, unemployment and minimum wage rises.

Keywords: wage differentials by skills, wage inequality, within-group wage inequality, between-group wage inequality, return heterogeneity, quantile regressions.
JEL codes: J24, J31, C21.

Résumé

Cet article étudie les évolutions des différentiels de salaire par niveau d'éducation pour les salariés (hommes) du secteur privé travaillant à temps complet, de 1976 à 2004. Nous appliquons la technique des régressions quantiles à des équations de type Mincer pour distinguer et décrire séparément les évolutions des inégalités inter- et intra-groupes d'éducation, ajustées par l'expérience. Nous utilisons une base de donnée résultant de l'appariement de données administratives et du recensement, et contenant des données annuelles.

Nos principaux résultats sont les suivants : (1) Les inégalités de salaire " globales " sont restées stables entre 1976 et 1992 et ont légèrement décrû entre 1995 et 2004. (2) Les inégalités intra-groupes augmentent avec le niveau d'éducation et sont plus élevées pour les diplômes généraux que pour les diplômes techniques et professionnels. (3) Les inégalités inter-groupes augmentent avec l'expérience. (4) Les inégalités intra-groupes sont restées stables entre 1976 et 1992, et ont diminué entre 1995 et 2004, particulièrement pour les moins expérimentés. (5) Les inégalités inter-groupes ont diminué tout au long de la période, en raison d'une baisse du rendement de l'éducation, particulièrement pour les moins expérimentés. Ces résultats sont mis en regard des évolutions importantes qu'a connues le marché du travail français durant cette période : remplacement des cohortes plus âgées par des cohortes plus éduquées, hausse du chômage et du salaire minimum.

Mots-clés : différentiels de salaire par niveau d'éducation, inégalités de salaire, inégalités inter-groupes, inégalités intra-groupes, hétérogénéité des rendements, régressions quantiles.
Codes JEL : J24, J31, C21.

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1 Introduction

This paper studies changes in wage differentials accross education groups for full-time male workers, in the French private sector, from 1976 to 2004. We use a matched dataset of yearly administrative data and Census information. We apply quantile regressions to Mincer-type equations to disentangle between- and within-education group wage inequalities and to describe separately their evolutions. Quantile regression estimates at various orders are used to compute measures of within-education group wage inequality adjusted for experience. For each education group, we compute the Q90-Q10, Q90-Q50, Q50-Q10 log wage differences adjusted for experience and adjusted Gini coefficients, that focus on what happens at the middle of the wage distribution. Between-education group wage inequalities are assessed by median wage comparisons.

Our results are the following: (1) the overall wage inequality was stable from 1976 to 1992 and slightly decreased from 1995 to 2004. (2) The within-education group wage inequalities increase with education and are higher for non-vocational degree owners. (3) The between-education group wage inequalities increase with experience. (4) The within-education group wage inequalities were rather stable from 1976 to 1992 and decreased between 1995 and 2004, strongly for low levels of experience. (5) The between-education group wage inequalities decreased all over the period, due to decreasing education premiums, particularly for low levels of experience. These results hold whatever the inequality measure used, whether student work periods are included in the sample or not, whether the experience accumulated since the first job spell or only the one accumulated since the end of studies is rewarded, whether the sample is restricted to 15-54 year old workers, or account for part-time workers. The same conclusions also remain when experience is replaced by age.

Quantile regressions are useful tools for analyzing the changes in the wage distribution and in the heterogeneity of the skill premiums. Whereas the OLS method gives only information on average returns, quantile regressions allow one to examine the whole conditional wage distribution. After the seminal paper of Koenker and Bassett (1978), Buchinsky (1994) was the first to investigate the sources of the U.S. wage inequality evolutions using quantile regressions. Since then, those methods have been applied to numerous countries[1] but rarely in France. The only papers we are aware of are Crépon and Gianella (1999) and Martins and Pereira (2004), the latter together with other European countries.[2] Both used the "Formation Qualification Profession" surveys (FQP), which took place in 1970, 1977, 1985, and 1993. They estimated Mincer-type equations, which included the number of years of education as a proxy for the educational attainment. They found that within-education group inequalities grow with the number of years of education. This feature is shared by most of Western countries, see also Lemieux (2006b). In this paper, we proxy the educational attainment by degree dummies. Seven degree categories are considered: no degree, basic high school, basic vocational, high vocational, general high school, some college, and university degrees. This flexible specification relaxes the linear relation between the number of years of education and the corresponding between and within wage inequalities. Finally, we find that

[1]See amongst others: Fortin and Lemieux (1998), Gosling, Machin, and Meghir (2000), Martins and Pereira (2004), Machado and Mata (2005), Autor, Katz, and Kearney (2005)

[2]Koubi (2005) uses quantile regressions for assessing between- and within- occupation age group wage inequalities.

the within-education group wage inequalities are higher for non-vocational degree owners than for those with a vocational degree and increase with the level of education for both types of degrees.

Moreover, we use more recent yearly data coming from the match between the DADS panel (déclaration annuelle de données sociales) and the EDP database (échantillon démographique permanent). With this new dataset, we can exploit information on working periods for each year between 1976 and 2004.[3]. Therefore, we precisely describe the wage distribution evolutions that occurred over 30 years. Concerning wage evolutions, our findings about decreasing between and within group inequalities – especially for low-skilled workers – confirm results of Crépon and Gianella (1999), and of other studies on French data, which focused on mean effects; see Goux and Maurin (1994), Bayet and Cases (1996), and Selz and Thélot (2003).

The baseline model considered in this paper is a classic Mincer one, with degree dummies and third-order effects of experience. However, we also consider an alternative specification, in which education and experience are interacted. This specification accounts for a non-separability of the two human capital types; see Rubinstein and Weiss (2006), Belzil (2006), Heckman, Lochner, and Todd (2006). The more educated workers usually get more easily training opportunities and promotions. They may be able to acquire or reveal skills faster than others. This may be related to education group unobserved abilities, or to an indirect effect of education. Experience is then apparently rewarded differently per education group, which accounts for the observed non-parallelism of the log-earnings experience profiles; see amongst others for the U.S., Murphy and Welch (1990), Murphy and Welch (1992), Autor and Katz (1999). Once allowing different education-group rewarding profiles of experience, it occurs that degrees used to have a direct positive impact on hiring wages in the 1970's and the 1980's, but this effect disappeared at the beginning of the 1990's – except for the university degree owners. Since then, the channel, through which education affects wages is strongly related to the experience rewarding profile and to the experience accumulation process. In terms of evolutions, the decreases of between- and within-education group wage inequalities that occured over the period are stronger for the less experienced workers than for more experienced ones.

These evolutions are related to the strong evolutions of the French labor market during this period: older cohorts gradually replaced by more educated ones, unemployment and minimum wage rises. The French evolutions differ from those of the U.S, where, since the 1970's, the overall inequality sharply increased. This trend has been driven by the top of the distribution since the end of the 1980's (see Goldin and Katz, 2007).[4] Numerous papers in labor economics describe and provide potential explanations to these dramatic evolutions; see amongst others, Katz and Murphy (1992), Juhn, Murphy, and Pierce (1993), Buchinsky (1994), Card and DiNardo (2002), Lemieux (2006a), and Autor, Katz, and Kearney (2008). In short, a consensus holds on the fact that the overall wage inequality increase is due to increases in education premiums, in within-group inequalities, and in average skill levels. However, the sizes of the contributions of these different channels and the explanations proposed are still in dis-

[3]Except 1981, 1983, 1990 and 1994.

[4]Two papers focus on a strong increase in top wages growth since the end of the 1990's in France but, at this stage, the stronger evolutions seem to occur only at the very top of the distribution – beyond the top 1% of the wage distribution (see Amar (2010) and Landais (2008)).

cussion. Skill-biased technological change (see Acemoglu, 2002, Autor, Katz, and Kearney, 2008), supply/demand effects (see Katz and Murphy, 1992, Card and Lemieux, 2001), composition effects (Autor, Katz, and Kearney, 2005, Lemieux, 2006a), minimum wage (Card and DiNardo, 2002, DiNardo, Fortin, and Lemieux, 1996) and deunionization (Card, Lemieux, and Riddell, 2004) are the main explanations proposed. In other western countries, the evolutions of education premiums and within-inequalities over the 1980's and the 1990's are very contrasted. The returns increased in Portugal (Machado and Mata, 2005), in Canada, and until the mid 1990's in the U.K (Card and Lemieux, 2001). They remained stable in Germany (Fitzenberger and Kurz, 2003) and in the U.K., on average since the mid 1990's (Walker and Zhu, 2008). They fell for Austria (Fersterer and Winter-Ebmer, 2003). The within-group inequalities increased in Portugal and in the U.K. (Gosling, Machin, and Meghir, 2000). They remained stable in Germany and in Austria.

The paper is organized as follows. Section 2 presents the data. The raw trends in wage inequalities, education and experience levels are described in Section 3. Section 4 is dedicated to the Mincer quantile regression model. The resulting between and within group inequality changes are presented in section 5. Section 6 describes between and within group wage inequality evolutions entailed by the alternative model, in which education and experience are interacted. Section 7 contains some sensitivity analyzes. Section 8 concludes.

2 Data

The data come from the match between the DADS panel (déclarations annuelles de données sociales) and the EDP dataset (échantillon démographique permanent).[5] The wage and experience variables are constructed using information from the DADS dataset and the education variables from the EDP dataset.

The DADS is an exhaustive administrative database of employer-employee wage-bill information, annually and compulsory filled in by any firm establishment. The DADS panel is an individual panel constructed from the DADS for scientific use. It contains information on all wages paid to, all working periods of, and all private sector employers of wage-earners born at some chosen dates. The EDP database collects census information (education, family status at the census dates, ...) and civil state administrative information (date of marriage, child birth, ...) of individuals born at some chosen dates. The exhaustive natures of both files enable one for matching information on individuals born in France. For people born abroad, the matching is not possible. The restriction to individuals born in France reinforces the likelihood that they attended school in France and then, were exposed to the French legislation concerning minimum age for leaving school. Some corrections applied to the data actually rely on this legislation.

[5]Those databases are produced by INSEE (French National Institute of Statistics and Economic Studies).

2.1 Variables

The variables used in the analysis are the wage (dependent variable), the highest degree obtained (education), and the experience accumulated as a wage-earner in the private sector. A detailed presentation of the variable construction is reported in the Appendix.

Wage variable

The wage variable is the real net daily wage in 2004 euros, that is, the sum of net earnings in real terms reported to the number of working days for a given working period.

Education variable

The highest degree obtained at the end of the studies is coded in 7 categories, which are reported in Table 1 with their shares in the panel population. These categories are very similar to the ones used by Abowd, Kramarz, and Margolis (1999).

Table 1: Degree categories

French label	English label	% (pooled sample)
Aucun diplôme déclaré or CEP, DFEO	no degree reported or completed elementary school	0.30
BEPC, BE, BEPS	completed junior high school	0.06
CAP, BEP, EFAA, BAA, BPA	basic vocational degree	0.37
Bac technique et professionnel, Brevet professionnel, autres brevets BEA, BEC, BEH, BEI, BES, BATA,	advanced vocational-technical degree (high vocational)	0.08
Bac général, brevet supérieur, CFES	completed high school	0.03
BTS, DUT, DEST, DEUL, DEUS, DEUG, diplôme professions sociales ou de la santé	some college, college degree and technical or vocational college	0.09
Dip. universitaire de 2ème ou 3ème cycle, diplôme d'ingénieur, Grandes Ecoles	university degree, engineering school, Grande Ecole	0.07

Experience variable

The experience variable refers to the experience accumulated as a wage-earner in the private sector. Its construction is mainly based on the exhaustive nature of DADS panel information. The experience variable sums up the shares of working days per year since the first occurrence in the panel up to the current working period. We do not make differences between experience accumulated when working during the studies and experience accumulated after the end of the studies. The experience variable so constructed combines both types of experience. In the sensitivity analysis, we also consider an alternative definition of experience, in which only the experience accumulated since the end of the studies is valuable.

School-leaving age and school-leaving year

The school-leaving age and the school-leaving year are required to determine whether a work period occurred before an individual finished his/her studies. School-leaving age and school-leaving year are collected in the 1968, 1975, and 1982 censuses but the question was suppressed in the 1990 and 1999 censuses and the annual census surveys 2004-2006. For the individuals concerned, we impute school-leaving ages by exploiting the empirical distributions of school-leaving age conditional on birth cohort, sex, and education, which were estimated using the French Labor Force surveys (LFS).[6] In order to check that this imputation does not affect the results, we consider some alternatives in the sensitivity analysis section.

2.2 The sample: full-time working periods of private sector male wage earners

The analysis is conducted for each year from 1976 to 2004, except for 1981, 1983, 1990 (because of missing data), and 1994 (because of the poor quality of the data).

The observation units are the working periods of the 15-64 year old male private sector wage earners born in France. In order to keep the wage distribution representative of the total number of days worked in the economy, the working periods are weighted by the number of working days they account for. Working periods corresponding to internships and apprenticeships are excluded from the analysis because their remunerations are often fixed and do not correspond to a valuation of skills such as in a Mincer-type equation. We also exclude student working periods principally because the level of education attained so far is unkwown. We only have information on the education attainment at the end of the studies.

Since 2004, the French exhaustive population census, which used to occur once a decade, has been replaced by annual census surveys, in which nearly 10% of the population are interviewed. So we use information from the 1968, 1975, 1982, 1990, 1999 censuses, and three annual census surveys 2004, 2005 and 2006. The latter roughly cover one third of the population. Consequently, education is collected for one third only of the individuals who finished their studies between 1999, the last exhaustive census year, and 2004. Hence we re-weight the observations that concern those individuals to avoid deformation of the per-year population structure.

The definition of the full-time/part-time variable changed in 1993-1994. Before 1994, it was directly collected. Since 1994, it has been automatically corrected: reported full-time workers with hourly wages smaller than 80% of the legal minimum hourly wage, are put in the part-time category. This change may entail breaks in the wage evolution especially at the bottom of the distribution for some education groups, even if the breaks do not clearly appear in descriptive statistics and Least Absolute Deviation (LAD) estimations. Consequently, we will not interpret evolutions all over the period, but only on the two subperiods 1976-1992 and 1995-2004. In the sample, between 4% and 7% of the observations per year are paid less than the monthly minimum wage of a full-time worker. Legally, a worker is considered

[6] To avoid memory bias, for each cohort, we consider LFS surveys when individuals are between 35 and 40.

working full-time if he is working strictly more than 80 % of the legal or conventional working time, see Demailly and Le Minez (1999). Finally, outliers are canceled out. We eliminate the observations such that $|\ln(\text{wage}) - q50| > 5 \times |q75 - q25|$ such as in Crépon and Gianella (1999). The sample used contains around 100,000 individuals and 45,000 observations per year.

3 Raw trends

3.1 Raw wage trends and wage inequalities

Figure 1 displays, for full-time male workers,[7] the overall evolutions of the log wage median, the log wage Q10 and Q90, and of related inequality measures: Q90-Q10, Q50-Q10, Q90-Q50 log wage differences, and finally, the Gini coefficient of the log wage distribution. From 1976 to 1992, the log wage Q10, Q90 and median increased: the Q10 rose by 0.14, the median by 0.10, and the Q90 by 0.11. From 1995 to 2004, the Q10 increased by 0.09 while the median and the Q90 increased by 0.04. The Q10 evolution is close to the French minimum wage evolution – this minimum wage is called *smic* for "salaire minimum de croissance" – also reported in Figure 1. Roughly speaking, the overall log wage inequalities, as measured by the Q90-Q10 log wage difference, were rather stable from 1976 (1.23) to 1992 (1.21). More precisely, from 1976 to 1984, the Q90-Q10 difference decreased by 0.04 driven by the decrease in the Q50-Q10 difference. During the same period, the minimum wage and the unemployment rate strongly increased. From 1984 to 1989, a period of economic growth, the Q90-Q10 difference increased by 0.03 driven by the increase in the Q90-Q50 difference. From 1989 to 1992, it slightly increased. Finally, the Q90-Q10 difference of log wages slightly decreased from 1.21 in 1995 to 1.14 in 2004, mainly as a result of a decrease in the Q50-Q10 difference – except some stability at the end of the 1990's. In contrast, the Q90-Q50 difference remained quite stable. In terms of wage levels, the wage Q90 was 3.4 times (=exp(1.23)) higher than the Q10 in 1976, whereas in 2004, it was 3.1 times higher than the Q10. The Gini coefficient draws a similar picture of the overall log wage inequality evolutions.

The Q99 and the Q99-Q90 log wage difference are also reported in Figure 1 to describe the top wage evolutions. Two recent French papers focus on a strong increase in top wages growth since the end of the 1990's. Amar (2010) and Landais (2008) show that the wage growth rate of wage earners above the Q99 has increased dramatically since the end of the 1990's. This event is likely to occur far beyond the top 1% of the wage distribution since the Q99 was rather stable over 1976-2004, the Q99-Q90 difference decreased between 1976 and 1992 and remained quite stable between 1995 and 2004.[8]

These evolutions are very different from those observed in the United States over the same period of time. In the U.S., the log of the Q90-Q10 weekly wage differences of full-time male workers increased by about 0.4, and the hourly log wage differences by about 0.2. The Gini coefficient – for annual earnings

[7] student working periods excluded.

[8] More precisely, the increase in Q99 between 1996 and 2000 was stronger than the increase in Q90 and Q50. This is consistent with Amar (2010)'s findings: a stronger increase in Q99 than in Q50 over the period 1996-2007, with two main periods of growth in top wages, 1996-2000 and 2006-2007.

in commerce and manufacturing – increased from 0.4 to 0.5. After a period of increasing inequality both at the top and at the bottom of the wage distribution from 1975 to 1987, inequality remained stable at the bottom while it continued to increase at the top until 2005, see Goldin and Katz (2007).

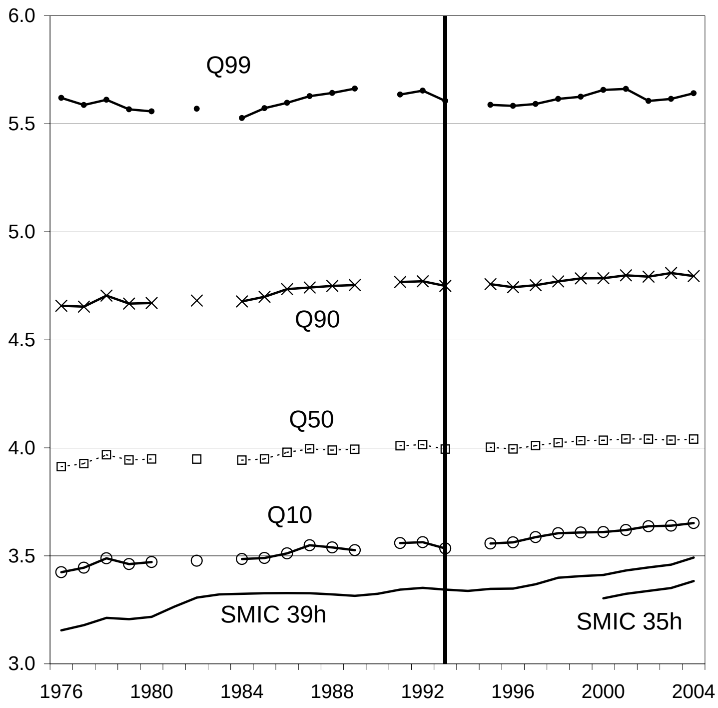
3.2 Education trends

From 1976 to 2004, the composition by education and experience of the French male labor force changed dramatically. Figure 2 displays the education trends for full-time male workers, students excluded. From 1976 to 2004, the education level strongly increased in France. Workers of older cohorts who were less likely to be educated were gradually replaced by more educated baby-boom cohorts. As an illustration, the proportion of male full-time workers with no degree or completed elementary school –aggregated in the "no degree" category– has fallen from 49% in 1976 to 21% in 2004. These trends are to be related to the succession of education policies during the 20th century. Two compulsory schooling laws increased the minimum school-leaving age: in 1936 from 12-13 to 13-14 and in 1959 from 14 to 16.[9] In addition, structural changes in the national educational system promoted the democratization of education. From 1976 to 1989, the proportion of workers with basic vocational degree increased from 30% to 40%, due to a widening of the access to basic education in the 1960's and the 1970's. Since then, changes in labor force education have principally occurred through increasing shares of high school, advanced vocational, and post-secondary degree owners. Once more, a political impulse led to these evolutions. In the mid 1980's, the government promoted the national objective to bring 80% of cohorts to the Baccalauréat level. A new vocational high school degree was created: the "Baccalauréat professionnel". Then, the share of male workers holding an advanced vocational degree increased from 6% in 1985 to 8% in 1999. The share of high school graduates remained stable over the period, around 4%. The real extent of democratization can be observed through the wider access to post-secondary education. The share of the labor force who attended college rose from 5% in 1985 to 11% in 1999, while the one graduated from university increased from 4% to 8%. Since 2000, the labor force educational composition has remained quite stable. This composition is not only driven by demographic evolutions but also by labor market policies. The 1993 cuts in low wages social contributions contributed to maintain low qualified jobs usually occupied by less educated people. The unemployment rate evolutions may also influence the educational composition of the working labor force since higher educated or higher experienced people are less likely to be unemployed.

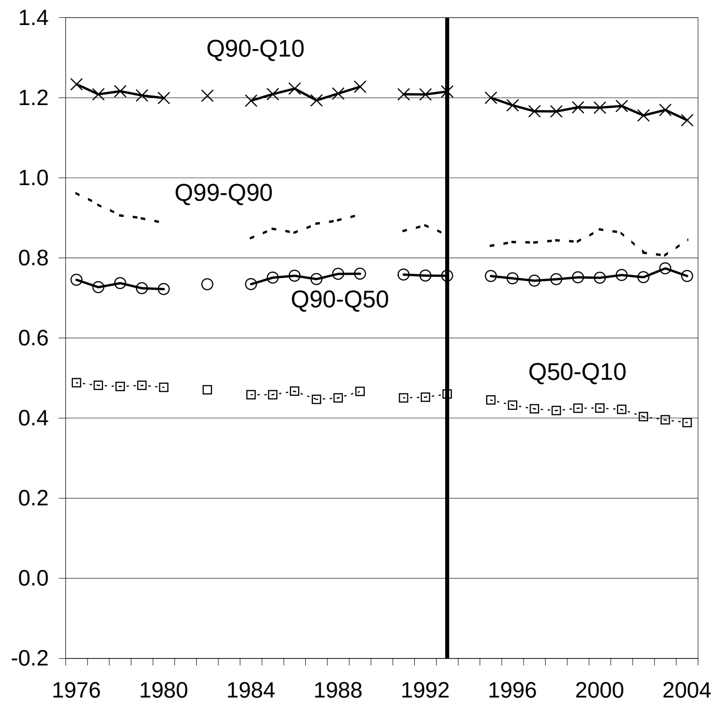
3.3 Experience trends

Figure 3 displays the experience trends of male full-time workers, students excluded. The average experience decreased from about 18 years in 1976 to 15.5 years in 1992, and remained quite stable from 1995 to 2004. The decrease in experience before 1992 is partly due to the increase in the school-leaving age

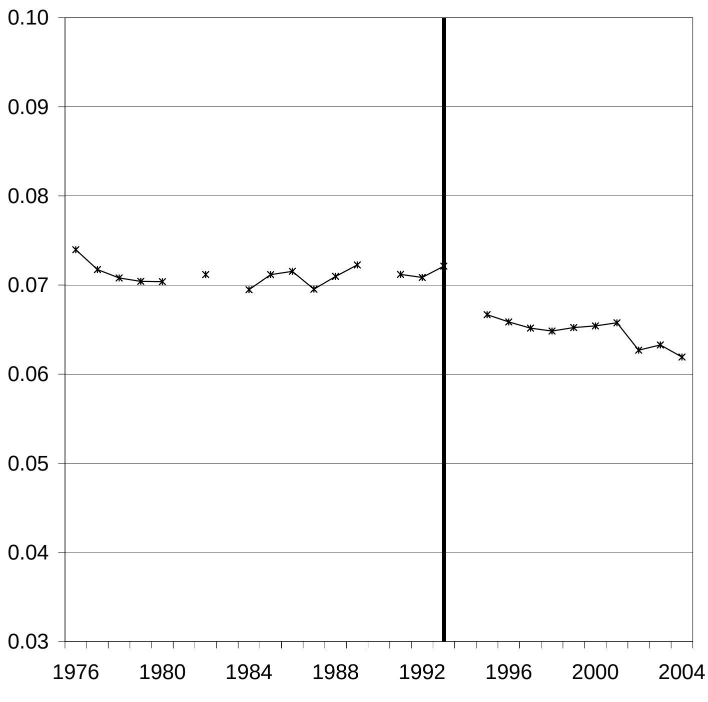
[9]Before 1936, individuals could quit school at 12 if they had completed a *certificat d'étude*, 13 if not. After 1936, both minimum leaving school ages were increased by one year. The Berthoin reform in 1959 established a unique legal minimum leaving school age at 16.



(a) Median, Q90, and Q10 of log wages



(b) Q90-Q10 log wages differences



(c) Gini coefficient of log wage distribution

Figure 1: Q10, Q50, Q90 of log wages, and inequality measures: full-time male workers.

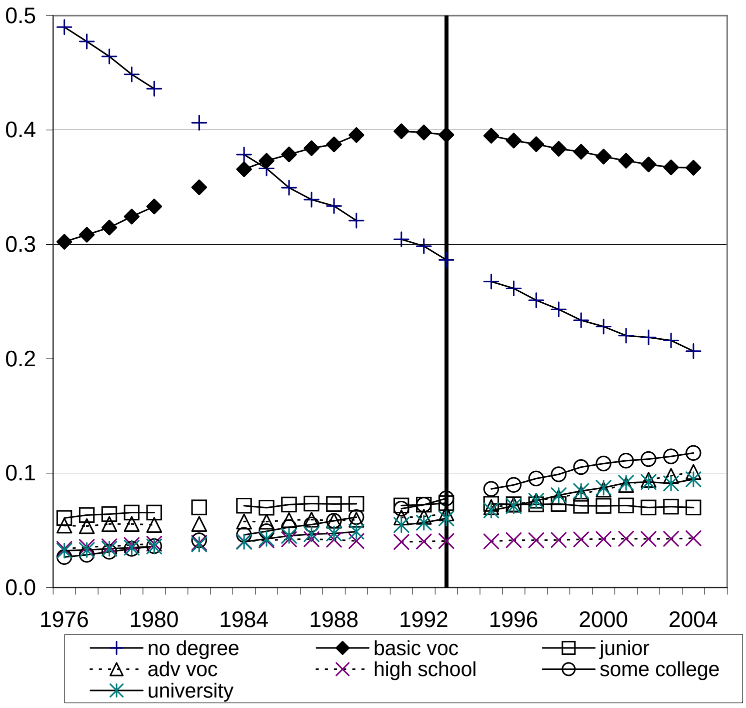
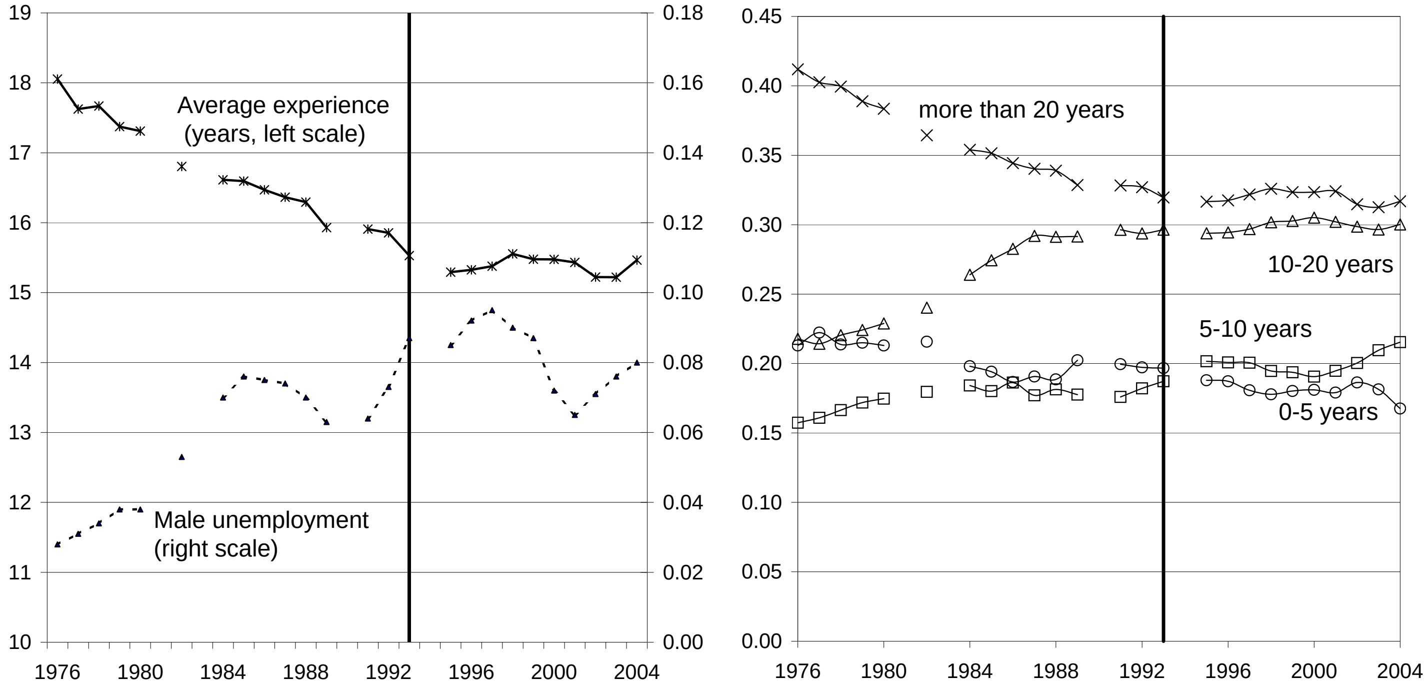


Figure 2: Educational attainment trends: full-time male workers.



(a) Average experience

(b) Shares of experience groups

Figure 3: Experience trends: full-time male workers.

and to the fact that seniors leave the labor market younger (pension reforms in the early 1980's and some pre-retirement schemes). When controlling for age and for education, the average level of experience is still much lower in 1992 than in 1976. That is to be related to the sharp increase in male unemployment from 2.8% in 1976 to 8.5% in 1993, see on Figure 3 the symmetric evolutions of male unemployment and average experience.[10]

To draw a more complete picture of the French wage inequality evolutions, one should investigate which part of those is related to evolutions of skill – education and experience – prices (between), which part is related to wage heterogeneity evolutions in a given skill group (within), and which part is due to composition effects. To disentangle between and within wage inequalities and to control for composition effects, we use quantile regressions on Mincer-type equations.

[10]To construct the experience variable for the older cohorts, we assumed that their careers were uninterrupted between the end of schooling and 1967. This might lead to a slight overestimation of their experience.

4 Mincer equation and quantile model

4.1 Model

We consider a Mincer-type model (Mincer, 1974), in which log daily wages are related to education and experience. Education is modeled by degree dummies and a 3-degree polynomial relation between log wage and experience is retained:

$$y_i = \alpha + \sum_{k=2}^{7} \beta_k \mathbf{1}_{dip_i=k} + \gamma_1 exp_i + \gamma_2 exp_i^2 + \gamma_3 exp_i^3 + u_i,\ i = 1, \ldots, N, \tag{1}$$

where y_i denotes the log daily real net wage of individual i for a given year (the year subscript is omitted); $\mathbf{1}_{dip_i=k}$ equals 1 if individual i has degree k, 0 otherwise [11]; exp_i denotes the experience as a wage-earner in the private sector; and u_i is the error term. When one is interested in describing the conditional wage mean or the between education-experience group wage heterogeneity, one usually assumes $E(u_i|dip_i, exp_i) = 0$ and performs mean regressions. However, mean regression models are not adapted to describe within education-experience group wage heterogeneity. To study the conditional wage distribution, we use the corresponding quantile regression model, (see Koenker and Bassett, 1978, Buchinsky, 1994):

$$Q_{y_i}(\theta|dip_i, exp_i) = \alpha_\theta + \sum_{k=2}^{7} \beta_{k\theta} \mathbf{1}_{dip_i=k} + \gamma_{1\theta} exp_i + \gamma_{2\theta} exp_i^2 + \gamma_{3\theta} exp_i^3,\ i = 1, \ldots, N, \tag{2}$$

where $Q_y(\theta|dip, exp)$ denotes the θ-order quantile of the conditional log wage distribution and θ belongs to $(0, 1)$. The slope parameter $\beta_{k\theta}$ measures the difference between the $\theta-$ quantile of the conditional wage distribution of those with degree k and and the $\theta-$ quantile of the one of those with no degree. If the covariates affect the whole shape of the log wage distribution, the impact of one covariate on tail quantiles may be very different from those on central quantiles, or on other parts of the conditional log wage distribution. Quantile regressions account for that form of conditional heteroskedasticity. However, one should note that the slope parameters $\beta_{k\theta}, k = 1, \ldots, 7$ cannot be interpreted as individual effects unless an additional order assumption is imposed – *i.e.* individuals are ordered the same according to conditional log wage for different values of covariates. Further, they cannot be interpreted as causal effects. Especially, no treatment is applied to account for possible endogeneity of the education and the experience variables. Finally, as noticed by Heckman, Lochner, and Todd (2006), $\beta_{k\theta}$ cannot be interpreted as the internal rate of return of schooling but as the price of schooling from a hedonic market wage equation since the costs of education are not taken into account. These are the reasons why, we prefer to call thereafter the slope parameters related to education, "premiums" rather than returns to education. Similarly for experience, we use the word "effects" rather than "returns" to experience.

[11] The degree dummies are: no degree or CEP (reference), junior high school degree, basic vocational degree, high school degree, advanced vocational degree, some college degree, and university degree. In a sensitivity analysis, we also perform regressions including working periods of students. In such cases, a new dummy "in studies" is added to the equation.

The quantile regression model is estimated separately for each year between 1976 and 2004 at various quantile orders.[12] Quantile regression estimates for orders .10, .25, .50, .75, and .90, and for years 1976, 1980, 1984, 1988, 1992, 1996, 2000, and 2004 are reported in Tables 2 and 3, together with corresponding OLS estimates. Standard deviations are obtained by design matrix bootstrap, see Buchinsky (1998).[13]

The quantile regression model covers the homoskedastic location model, the location-scale model, and a large range of conditional heteroskedastic models. In vectorial notation, equation (2) entails:

$$Q_{y_i}(\theta|x_i) = \alpha_\theta + \delta_\theta x_i,\ i = 1, \ldots, N,\ \theta \in (0,1) \tag{3}$$

where δ_θ is the slope parameter vector, and x_i stands for the covariates appearing in equation (2) but the constant. If the true model is the homoskedastic location model – also simply called location-shift model – or the location-linear in scale model, closed forms for quantile parameters can easily be derived. If the true model is the homoskedastic location model, $y_i = \alpha + x_i\delta + u_i,\ u_i \overset{iid}{\sim} F,\ i = 1, \ldots, N$, then $\alpha_\theta = \alpha + F^{-1}(\theta)$ and $\delta_\theta = \delta$. The slope parameters for different quantiles are equal. Covariates only affect the central tendency of y, not its heterogeneity. If the true model is the location-linear in scale model, $y_i = \alpha + x_i\delta + (x_i\zeta)u_i,\ u_i \overset{iid}{\sim} F,\ i = 1, \ldots, N$, then $\alpha_\theta = \alpha + F^{-1}(\theta)$ and $\delta_\theta = \delta + F^{-1}(\theta)\zeta$. We perform specification tests for those two sub-models. We use simple Wald tests to test for a homoskedastic location model such as proposed by Koenker and Bassett (1982), and Khmaladze-type tests based on the entire quantile process such as proposed by Koenker and Xiao (2002) for testing both the location-shift and the location-linear in scale model hypotheses. We both consider the joint hypotheses and univariate sub-hypotheses. For the Wald tests, the null hypothesis is equality of quantiles parameters at order .10, .25, .50, .75 and .90. To construct Koenker and Xiao (2002) tests for location-shift and location-scale-shift models, quantile regressions were performed at orders .10 to .90 by a .05 step. The critical values we use are those reported in Table B.1. and B.2. p 318 in Koenker (2005). Quantile regressions and tests were performed in R with the quantile regression package `quantreg`, see Koenker (2005). Inference results are reported in Table 4 in the appendix. The location-shift model is always rejected at 5% by Wald tests as well as by Khmaladze tests whereas Khmaladze tests do not often reject the location-scale-shift model at 5%.

4.2 Tools for the analysis

We exploit the quantile estimates to construct several descriptive tools. The education premium median –LAD– estimates are used to describe the between-education group inequalities whereas the education premium quantile estimates at other orders give information on within-education group inequalities. Similarly, the fitted values of the quantiles of the log wage conditional distribution, in short the adjusted wage distribution, give information on the within wage inequality for a given education group and adjusted for experience. As within inequality measures, we use Q90-Q10, Q50-Q10, Q90-Q50 adjusted log wage differences. In order to stress what occurs at the middle of the distribution, we also compute adjusted Gini

[12] Except for 1981, 1983, 1990 because of a lack of data, and for 1994 because the data is not reliable.

[13] The potential correlation between years or between working periods for a same individual is not accounted for.

coefficients, as suggested by Koenker (2005). A detailed presentation of the Gini coefficient computation is reported in the Appendix.

Results on education wage inequalities and premium heterogeneities adjusted for experience are discussed in the three following sections with graphical representations to stress evolutions. Wald tests are used to test whether those evolutions were significant, under an independence assumption of the samples pertaining to two different years.

5 Wage inequalities by education groups

In this section, we present the wage inequalities estimates by education groups adjusted for experience entailed by equation (2).

5.1 Between-education group inequalities

Figure 4 displays the log wage premium estimates at the median, i.e. the LAD estimates, for each degree and the corresponding adjusted log wages with 0 years of experience.

From 1976 to 1992, the adjusted log wages of each education group increased –strongly for the lower degrees, not significantly at a 5% level for some college and university degrees. They slightly decreased from 1995 to 1998, and then increased again. The overall effect over 1995-2004 differs between education groups: adjusted log wages increased for the no degree and the basic vocational degree groups, remained stable for the junior high school degree group and decreased for the other education groups.

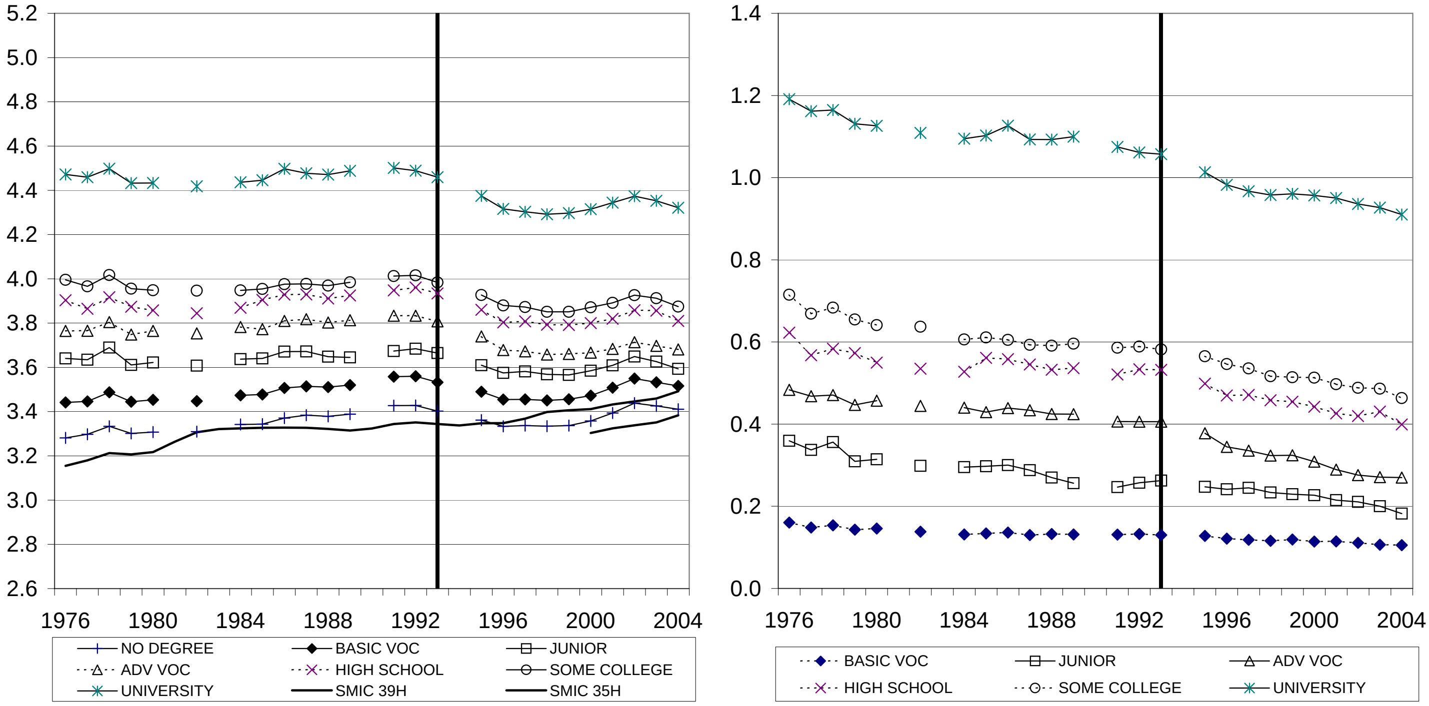
Wage differences can be studied by analysing the degree premiums (relative no degree). The degree premiums decreased and got closer to each other over the period. They mainly decreased between 1976 and 1984 and between 1995 and 2004 and, the decline was stronger for the higher degrees since the mid 1990's. Consequently, the inequalities between education groups –adjusted for the level of experience – decreased.

We also ran an estimation with a third-order polynomial in age rather than in experience (see Figure 15 (a) in the appendix). Results for between-education group inequalities are quite the same.

5.2 Within-education group inequalities

To investigate the within-education group wage inequalities, we consider adjusted wages at different points of the wage distribution. Figures 5, 6, and 7 display the Q10, Q50 and Q90 log wages adjusted for experience –that is computed with 0 years of experience– for the different degrees.

Cross section
The adjusted wage inequalities are always higher for non-vocational degrees (university, high school,



(a) Q50 (LAD) adjusted log wages

(b) Q50 (LAD) premiums

Figure 4: Model (2): LAD premiums (relative to no degree) and median log wages adjusted for 0 years of experience.

and junior high school degrees) than for vocational ones.[14] Within a type of degree (vocational or non-vocational), the higher the education level, the higher the adjusted wage inequality. This result extends the ones of Crépon and Gianella (1999) or Martins and Pereira (2004), who use the number of years of education as a proxy for the education level. They found that the higher the education, the higher the wage inequality. Here, we stress that this is true but once the kind – vocational or general – of education is controlled for. For instance, the within junior high school group inequality is higher than the one of the advanced vocational group.

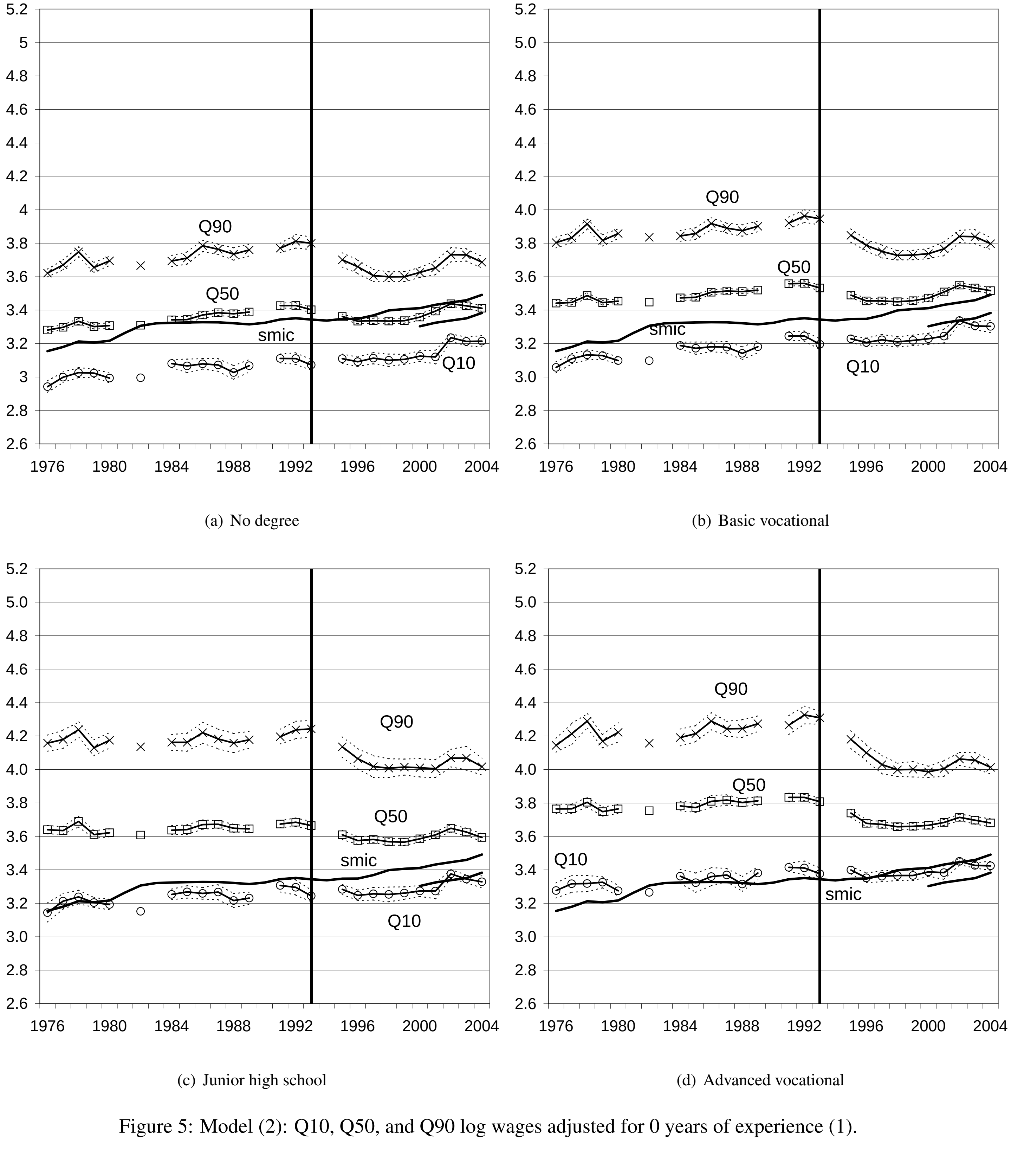
What happens at the tails of the wage distribution? For vocational degrees, the within- inequalities at both tails of the wage distributions increase with the level of education. This is no longer true for the non-vocational degrees at the top since the strongest wage inequality at the top occurs for high school degrees.

Evolutions
The change in the full-time worker dummy construction that occurred in 1993 prevents one to make comparisons over the two sub-periods 1976-1992 and 1995-2004. The Q90-Q10 adjusted log wages differences were quite stable until the mid of the 1990's. They decreased from 1995 to 2004 –not significantly for high school and university degree owners. To give some figures, a college graduate at the Q90 of the conditional wage distribution earned in 1976 3.6 times more than one at the Q10 with the same level of experience versus 3.2 in 1992. In 1995, he/she earned 2.8 times more versus 2.6 times more in 2004. In contrast, a worker with no degree at the Q90 earned 2 times more than one at the Q10 in 1976 versus 1.8 in 1992, and 1.8 in 1995 versus 1.6 in 2004. Figure 8 reports the evolutions of the adjusted Gini coefficients as alternative inequality measures. Results about within-education group inequalities evolutions are the same.

The evolutions of the Q50-Q10 and the Q90-Q50 adjusted log wage differences compensated each other between 1976 and 1992 and presented quite similar patterns at the end of the period. From 1976 to 1992, the within-education group wage inequalities slightly increased at the top (significantly at 5% only for advanced vocational degrees) whereas they slightly decreased at the bottom (not significantly at 5% for no degree, junior high school and advanced vocational groups). From 1995 to 2004, they slightly decreased at both tails of the distribution (not significantly at 5% for university degrees, and high school degree at the top). Yet the decrease at the top principally occurred between 1995 and 1998 and was driven by a decrease of the Q90, while the decrease at the bottom occurred all over the period. Figure 7 (c) reports the shares of the overall log wage inequalities attributed to the bottom of the wage distribution. These shares were higher than 0.4 whatever the degree in 1976 – .64 for university. They decreased until 1992 for any degree. So the inequalities at the bottom of the wage distribution had contributed less and less to the overall inequality, and this decrease was the most pronounced for the university degree. From 1995 to 2004, the contributions of the bottom were around .55 for the university degree and .45 for the other degrees. The evolutions of the adjusted wage inequalities are quite similar between education groups.

[14]The some college category is a mix of some vocational and non-vocational degree owners, which are impossible to distinguish in the data. The corresponding premium heterogeneity reflects that mix position. It relies between the purely vocational degrees and the purely non-vocational ones.

Results for the specification with the age instead of the experience give similar conclusions (see Figure 15 (b) in the appendix).



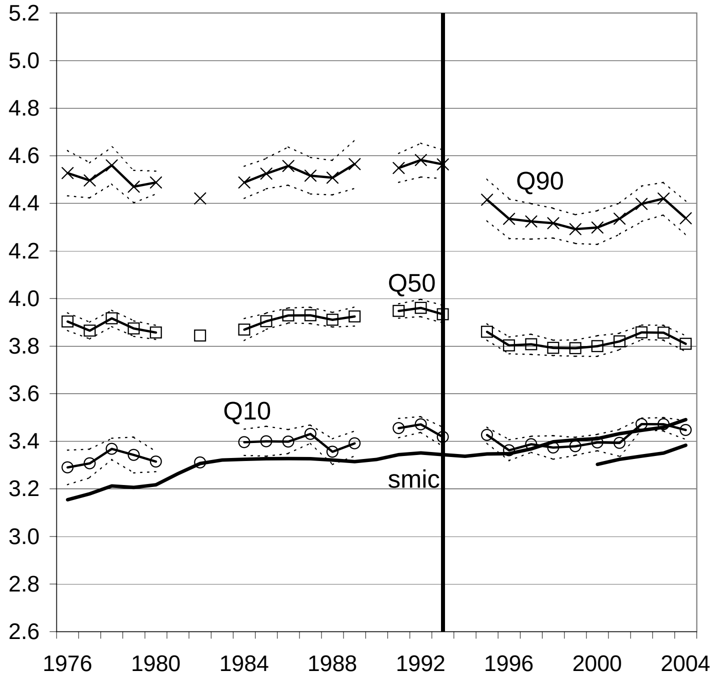
(a) No degree

(b) Basic vocational

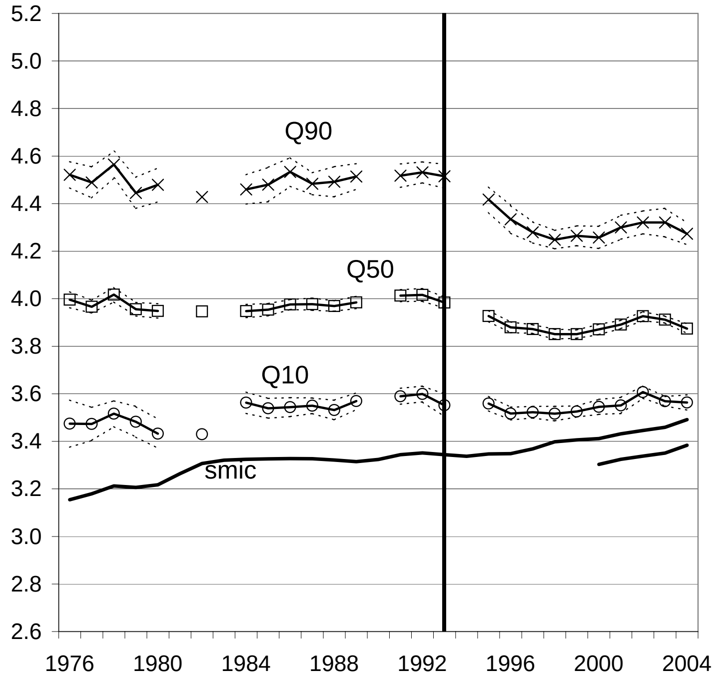
(c) Junior high school

(d) Advanced vocational

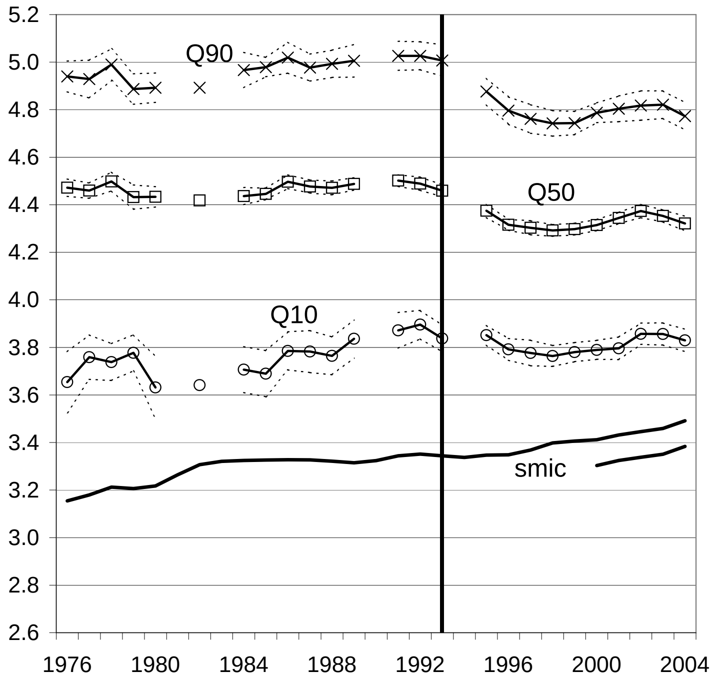
Figure 5: Model (2): Q10, Q50, and Q90 log wages adjusted for 0 years of experience (1).



(a) High school

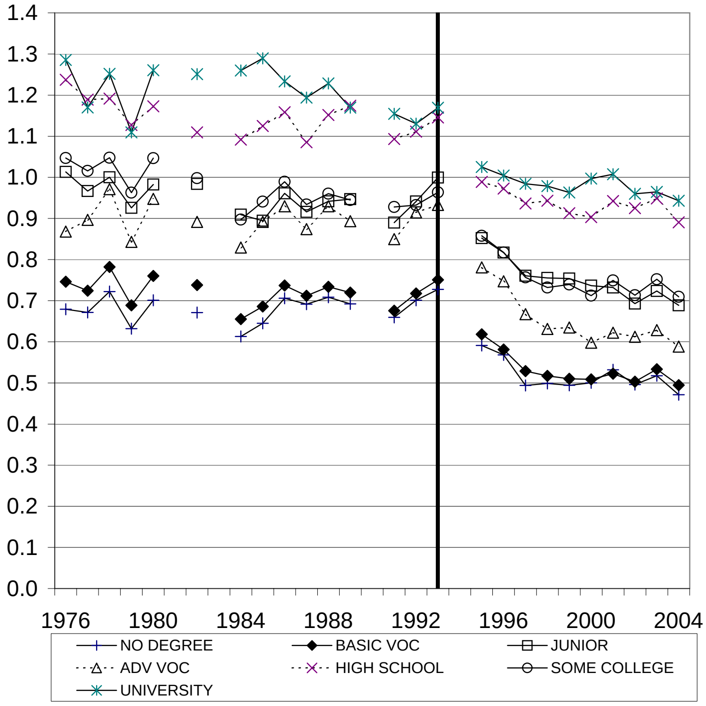


(b) Some college

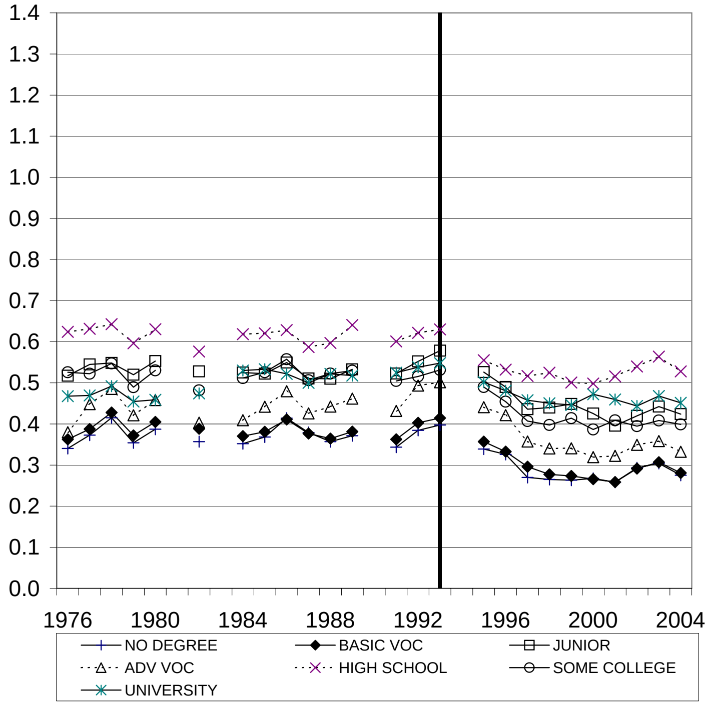


(c) University

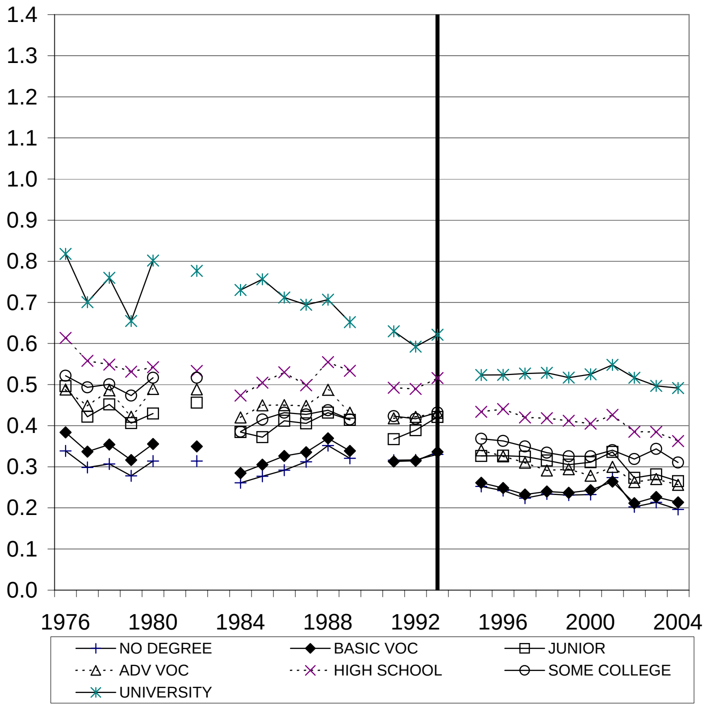
Figure 6: Model (2): Q10, Q50, and Q90 log wages adjusted for 0 years of experience (2).



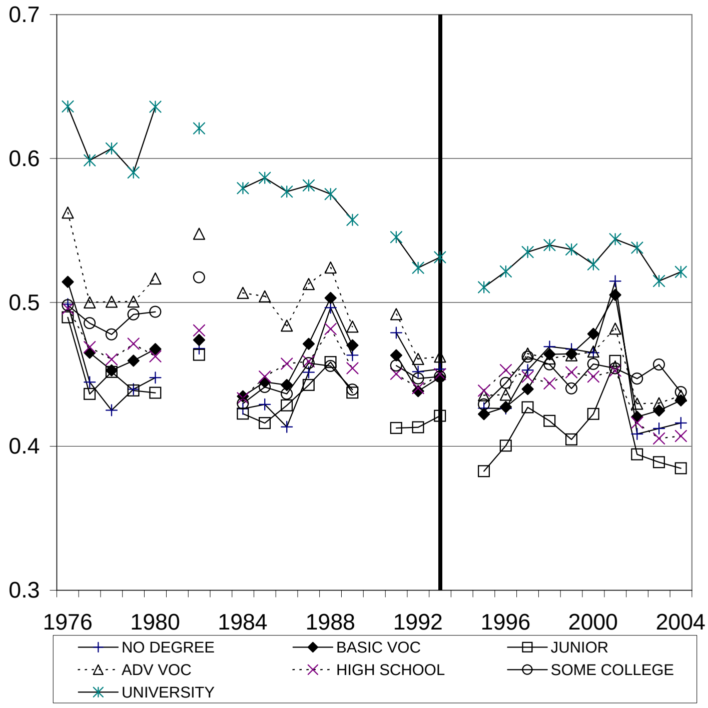
(a) Q90-Q10 log wages differences



(b) Q90-Q50 log wages differences



(c) Q50-Q10 log wages differences



(d) Share of Q50-Q10 log wages differences in Q90-Q10 difference

Figure 7: Model (2): Q90-Q10, Q90-Q50, and Q50-Q10 log wage differences adjusted for 0 years of experience.

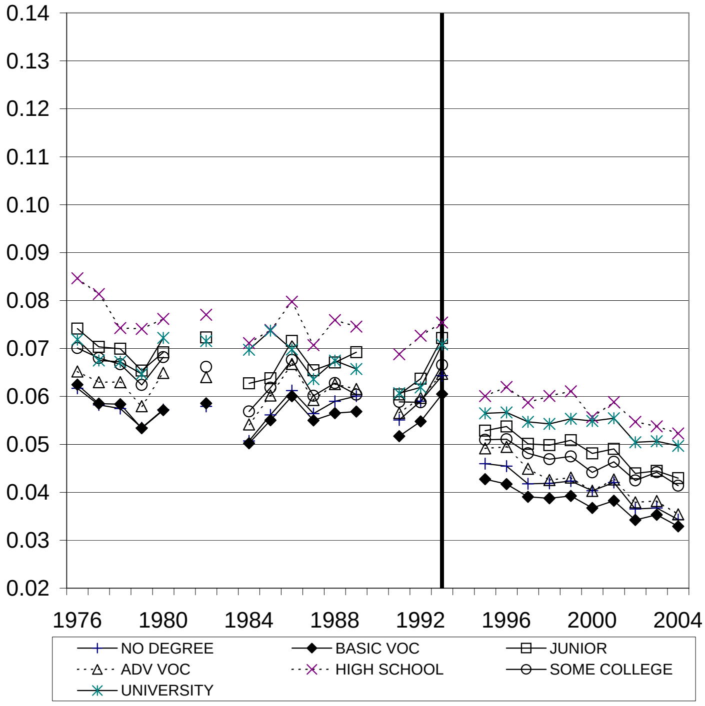


Figure 8: Model (2): Gini coefficients of log wage distributions adjusted for 0 years of experience

5.3 Discussion

Our main results are the following: the between-education group wage inequalities decreased due to a decline in education premiums over 1976-2004. The within-education group wage inequalities increase with education whatever the year (cross section) but, it decreased over time from 1995 to 2004, most strongly for the less educated workers.

Several factors may explain the increase in the within-group wage inequalities with the level of education. First, the degree category chosen may be more and more heterogenous as the level of education increases. For instance, the range of degrees included in the "university" category is probably larger than the one of those contained in the "high school" category.

Another explanation may be that the returns to unobserved components are more heterogenous for higher levels of skills. Low-skilled workers may have jobs with pre-defined or repetitive tasks, which do not permit to reveal their abilities and for which wages are fixed, while high-skilled workers may be more autonomous, more often paid for performance (see Lemieux, MacLeod, and Parent, 2009), and with an individual bargaining power.

Martins and Pereira (2004) retain an over-education argument. Over-education is more likely to occur for high levels of education than under-education for low levels. This unbalance may entail higher within-group inequalities for groups with higher education than for groups with lower one. However, for Spain, Budría and Moro-Egido (2008) find that the positive association between post-secondary education and earnings within-group dispersion hinges on other factors than educational mismatch.

Besides, three main features of the labor market can explain a large part of our findings: minimum wage rises, unemployment evolutions and labor force educational attainment.

On the whole period, the minimum wage rose and became more binding (Demailly and Le Minez, 1999). The evolution of the median adjusted wage for workers with no degree was quite similar to the one of the minimum wage, except on the period 1995-1998 (see Figure 4). Between 1976 and 1983, the minimum wage strongly increased, particularly in 1981 and 1982 when the Government rose it greatly above the level automatically predicted by the legislation ('coup de pouce'). As a result, in 1982, 7.8% of no degree workers and 3.5% of university degree owners were paid at the minimum wage. A sharp slowdown occurred between 1983 and 1996 and, the minimum wage remained roughly stable –except an increase between 1989 and 1992. Since 1997, the minimum wage strongly increased again (Carcillo and Delozier, 2004). In 1997, another 'coup de pouce' occurred. Further, the legal working time reduction from 39 hours to 35 hours a week introduced in 1998 was accompanied by a strong hourly minimum wage rise. As the new working time had not been applied in every firm at the same date, quite an important number of workers remained at 39 hours and their monthly wages increased, see Koubi and Lhommeau (2007).

Minimum wage may tighten the bottom of the wage distribution through several channels. (1) Workers with productivity lower than minimum wage are not employed. (2) Minimum wage prevents firms to push down wages for less educated workers with low bargaining power and thus reduces the heterogeneity at the bottom. (3) A minimum wage rise an increase in wages for workers paid at the minimum wage level, a weaker increase for the workers whose wages are caught up by or close to the minimum wage (spill-over effects), and in contrast, high-paid workers are little or not affected. (4) "Low-wage traps" may have occurred since the 1990's: firms have been incited to hire at the minimum wage to benefit from exonerations.

These minimum wage effects are probably stronger for low-degree workers. They may explain the lower within-education group wage inequalities for the less educated all over the period. Furthermore, the strong minimum wage increase over the period may have also entailed the within-education group wage inequalities decline at the bottom. Moreover, a minimum wage increase may reduce the wage gap between the workers paid around the minimum wage and the others. The evolutions of the minimum wage may thus explain the decreasing education premiums. Between 1976 and 1982 and between 1996 and 2004, the education premiums strongly decreased while the minimum wage strongly increased, (see Carcillo and Delozier, 2004 for additional figures on the minimum wage evolutions). Furthermore, the decreases in premiums ended first for the basic vocational group, who have lower wages and are probably caught up earlier by the minimum wage than the others.

Unemployment can also explain a part of our results. An unemployment increase may induce a selection effect: in an education-group, only the more productive remain employed and the distribution of the unobserved skills is shifted to the right. Unemployment strongly increased between 1980 and 1985 and between 1991 and 1994. Then, it remained over 8% between 1993 and 1999 (see Figure 3 (a)). It increased early and strongly for the less educated and it truely affected the more educated workers only since the economic crisis in 1992-1993 (see Figure 13 (a) in the appendix). As the low-skilled workers are more likely to be unemployed than the high-skilled ones, the selection effect of unemployment could be higher on the former. This could explain the lower within-group wage inequalities for lower levels of education, whatever the period. The strong increase in unemployment, stronger for the less educated workers, can also explain the decreasing returns to education and the decreasing within-education group wage inequalities all over the period. However, the selection effect of unemployment is not totally convincing. From 1991 to 1993, the unemployment strongly increased and from 1995 to 1998, it remained very high and, neither the Q10 nor the Q50 adjusted wages increased on those periods, whatever the degree considered.

Unemployment and minimum wage effects could interact: unemployment may put downward pressure on wages and this pressure may be stronger on high wage workers than on low wage workers for whom the minimum wage binds their wages (Fondeur and Minni, 2004). This entails stronger premium decreases for the more educated. This can explain the 1995-1998 within-heterogeneities decreases at the top found for all degrees, and which were stronger for the more educated, for whom the Q10 also decreased. The selection effect of unemployment combined with the increase in the minimum wage may have outweighed the unemployment pressure on wages at the bottom of the wage distribution for low-degree owners. The Q10 for no diploma, basic vocational and junior high-school workers remained indeed roughly stable between 1995 and 1998.

The increase in educational attainment may also explain the falls in skill premiums through a classic supply-demand effect: the increase in labor demand did not compensate the increase in labor supply of skilled workers. When a skill becomes more frequent, its price diminishes. The fact that the degree share increases and the decreases in education premiums occured at the same time sustains this explanation, especially for secondary and post-secondary degrees (see figure 2). The U.S. experienced similar patterns in the past: Goldin and Katz (2007) find that the narrowing of the U.S. wage structure between 1910 and 1950 entailed by decreasing education premiums are linked to a sharp increase in educational attainment. The increase in secondary and post-secondary educational attainment could also have entailed an increase of the diversity of degrees at those levels and an increase in the unobserved ability heterogeneities. This may partly explain why the decrease in within wage inequalities are lower for those degrees between 1995 and 2004.

The Q10, Q50 and Q90 quantiles of the unconditional log wages distribution kept increasing between 1995 and 2004 whereas the adjusted Q10, Q50 and Q90 log wages quantiles increased only for the less educated workers during this period. Consequently, most of the increase in average wages over the period has resulted from increased levels of education. This also suggests a strong contribution of education to productivity changes over the same period. We must recall however that the present study focuses on net wages. Our results remain therefore compatible with additional changes in productivity unexplained by education that would have been captured by increases in social contributions all over the period.

Finally, sector selection effects that had changed during the period may have modified the supply/demande equilibrium and drive a part of the results. (1) Since 1976, self-employment has dramatically decreased and the share of wage earners among workers has increased, partly due to the decline in the number of farmers (see Tavan, 2008). (2) The share of public services in total employment sharply increased until the mid of the 1980's and more slowly after. Between 1985 and 2003, public sector employment increased by 20% while total employment increased by 15% (see Tavan, 2008). (3) Furthermore, female labor market participation sharply increased over the period: the share of women in total employment was 41% in 1982 and 49% in 2004. (4) Part-time working periods are excluded from the analysis. The share of part-time workers increased since the mid 1970's: for men, 2.5% in 1982 and 5.6% in 1998 (see Cette, 1999). However, the effects of these changes may be mixed.

6 One step further: interacting education and experience

In this section, we consider an alternative specification, in which degree dummies and experience are interacted. This enables us to study the within and the between education group wage inequalities at different levels of experience and their evolutions. More precisely, we consider

$$Q_{y_i}(\theta|dip_i, exp_i) = \sum_{k=1}^{7}(\beta_{k\theta} + \gamma_{1k\theta}exp_i + \gamma_{2k\theta}exp_i^2 + \gamma_{3k\theta}exp_i^3)\mathbf{1}_{dip_i=k},\ i = 1, \dots, N, \tag{4}$$

Quantile regression estimates at orders .10, .25, .50, .75, and .90, and for years 1976, 1980, 1984, 1988, 1992, 1996, 2000, and 2004 are reported in Tables 5, 6, 7, 8, 9 and 10 in the appendix. OLS estimates are also reported. Tables 11 and 12 contain the inference results. The location-shift model is always rejected at a 5% level by Wald and Khmaladze tests. Khmaladze tests often reject the location-scale-shift model at a 5% level, mainly before the 1990's.

Model (4) allows for a sort of a non-separability between both types of human capital– i.e. education and experience, which illustrates the fact that for instance more educated workers usually get more easily training opportunities and promotions.[15] This nonseparability may be induced by the fact that more educated workers may be able to acquire or reveal skills faster than others because of unobserved abilities, or because of an indirect effect of education. Again, the question here is not to identify a causal effect of education but to describe how different education-group experience rewards affect education group wage heterogeneities and how they have changed since the 1970's.

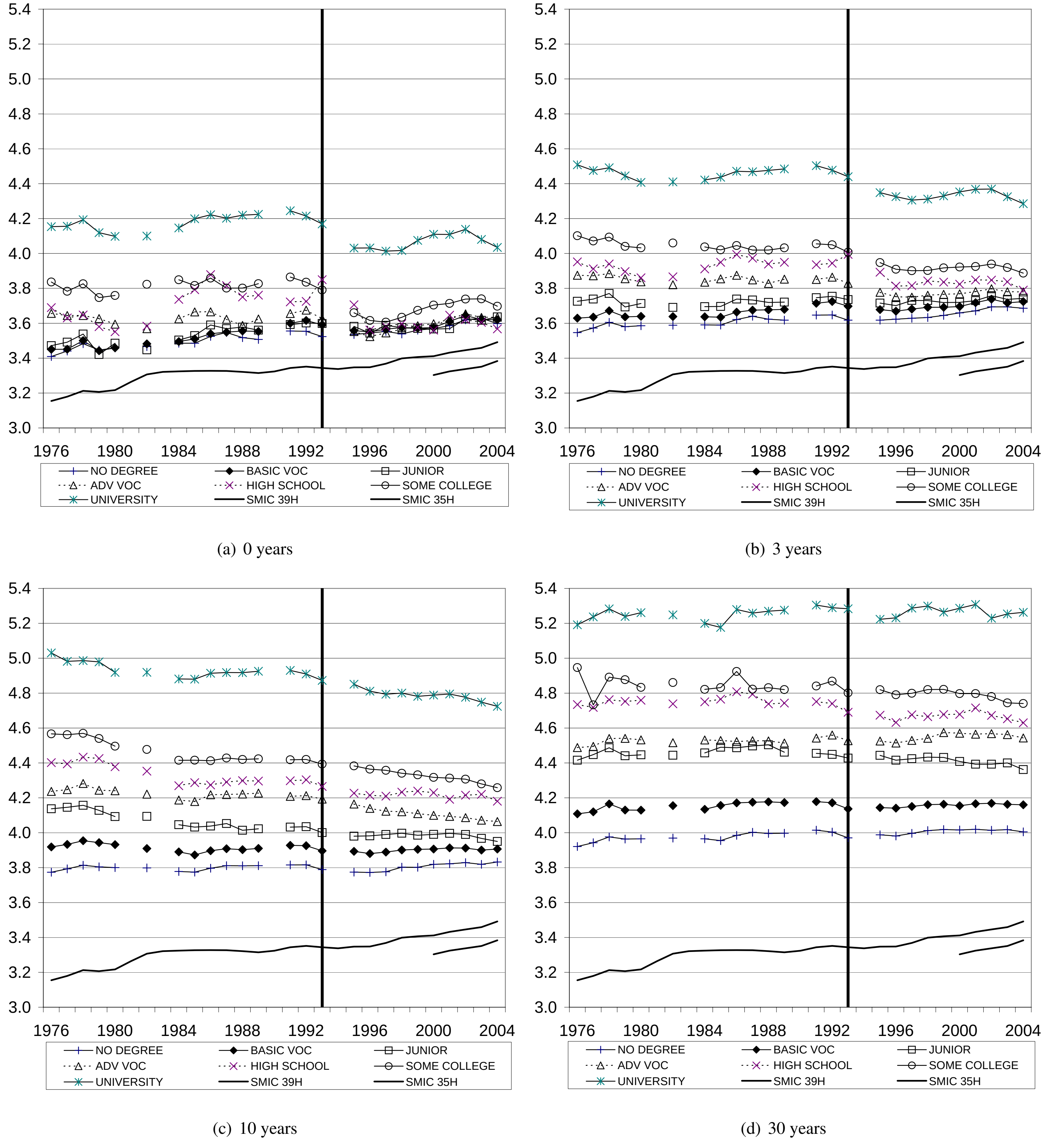
6.1 Between-education group inequalities

Figure 9 displays the LAD adjusted log wages for the different education groups at 0, 3, 10, and 30 years of experience. First, the between-education group wage inequalities increase with the level of experience. In other terms, apparent experience rewards are higher for more educated workers. Once allowing different education-group rewarding profiles of experience, it occurs that adjusted log wages at hiring (0 year of experience) have not been significantly different from one another since 1992 – except for the some college and the university degree owners. In other words, the degree used to have a direct positive impact on hiring wages in the 1970's and the 1980's, but this effect disappeared at the beginning of the 1990's – except for the university degree owners. Since then, the channel, through which education affects wages is more related to the experience rewarding profile and surely the experience accumulation. More generally, in terms of evolutions, the between-education group wage inequalities decreased between 1976 and 2004, more for the less experienced workers than for the more experienced ones. Note that at 30 years of experience, the between-education group wage differences have remained rather stable all over the period. In order to compare the education group experience rewarding profiles, we report the LAD estimates of the marginal effects of experience by education groups for 1976 and for 2004; see Figure 14 in the appendix. For a given education group, the marginal effects of experience decrease with experience – except for the university degree owners at the end of career in 1976. Between education groups, marginal effects of experience increase with the level of education at least up to 10 years of experience. However, the profiles are different according to the degree. When comparing 2004 to 1976, it appears that the marginal effects of experience heterogeneity decreased for the low levels of experience but in 2004, the marginal effects of experience remained positive up to 40 years of experience – except for the some college group, whereas they cancelled out and became negative beyond 25 years of experience in 1976. This positive "until the end" effect of experience may be related to the selection process faced by older/experienced workers on the labor market.

6.2 Within-education group inequalities

Figure 10 displays the Q90-Q10 adjusted log wage differences by education group at different levels of experience and Figure 11 displays the corresponding Gini coefficients. Most of the stylized facts about within-inequalities established using the simple Mincer-type model (equation (2)) remain the same.

[15] see Rubinstein and Weiss (2006), Belzil (2006). Heckman, Lochner, and Todd (2006)



(a) 0 years

(b) 3 years

(c) 10 years

(d) 30 years

Figure 9: Model (4): LAD-median log wages estimates at various levels of experience.

(1) The within-education group inequalities are higher for non-vocational degree owners than for those with a vocational degree, except at 0 years of experience and for some years before 1995. Among the vocational degrees, the higher the education level, the higher the adjusted wage inequality. This is less obvious for non-vocational degrees: the within-inequalities are lower for junior high school degree owners than for high school and university graduates, but the sorting between the two latter is less clear.

(2) The within-education group inequalities decreased from 1976 for the no degree and the basic vocational degree groups. Since 1995, they decreased for most degrees and levels of experience, especially in the less experienced groups.

6.3 Discussion

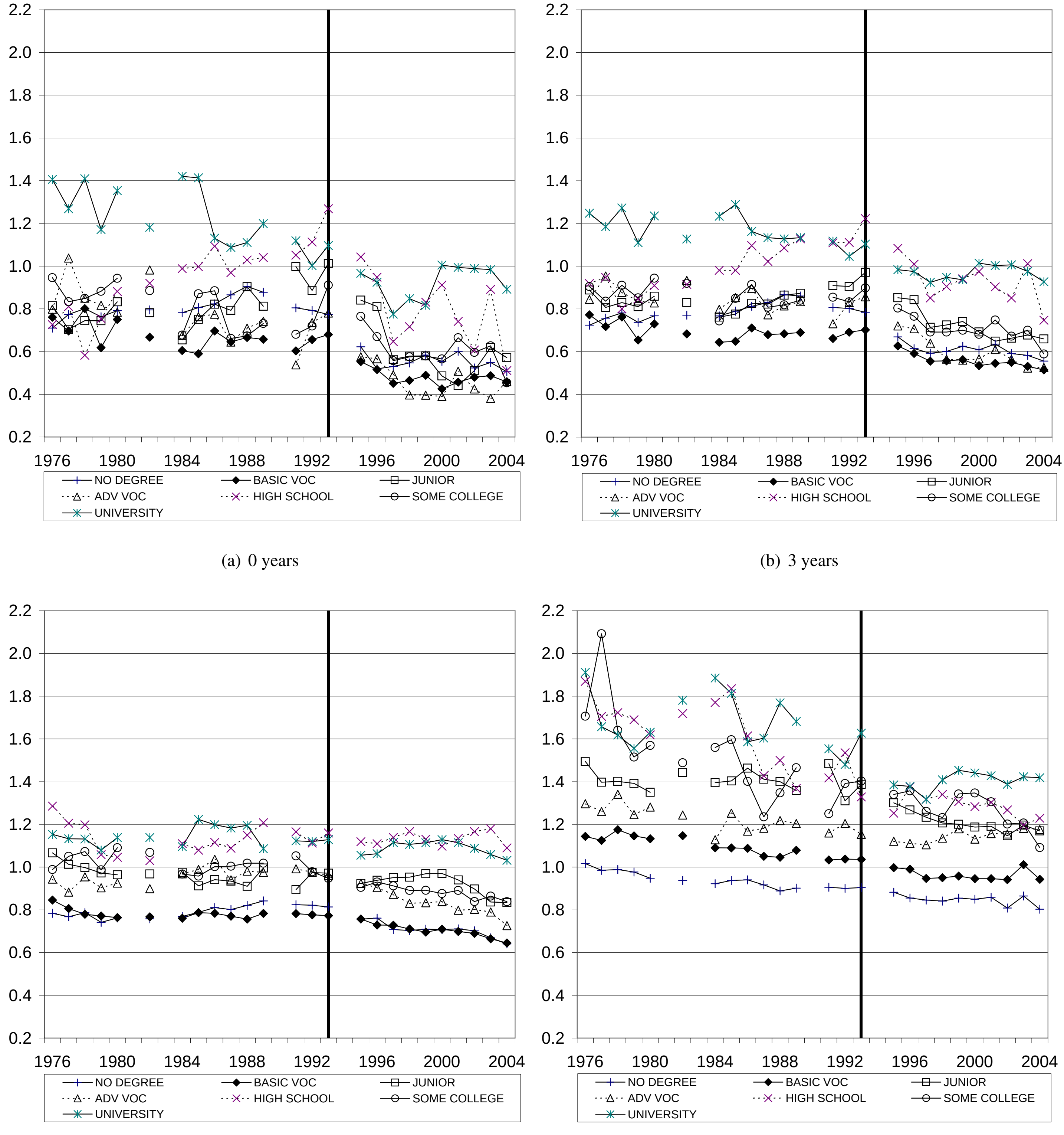
The between-education group wage inequalities increase with the level of experience, particularly for experience levels below 10 years of experience. Several explanations can be proposed. The more educated workers may acquire quickly new skills, either because a higher level of education provides higher abilities to acquire new skills, or because a higher level of education is a signal of higher unobserved skills. If these skills are firm specific or sector specific human capital, the more educated workers may have higher returns to seniority. If these skills provide a transferable general human capital, they may have higher returns to experience. Their past work spells could have been also more remunerated if their mobilities are more often voluntary, for example during the search of the best matches at the beginning of the career. For the less educated, the unemployment pressure on wages and the "low-wage trap" reduce the wages difference between different levels of experience. Moreover, mobility is more likely to be a negative signal for those workers, because it's more often involuntary (end of short-term contracts for example). Yet, one must be cautious in interpreting these stylized facts as a causal effect of education on wage career because they can also be due to cohort effects.

The tightening of the wage distribution observed was stronger for the less experienced workers. Both the between-education group wage inequalities and the within ones decreased for the latter over the period. Unemployment, minimum wage and supply/demand effects are serious candidates to explain these findings.

The wage moderation that occured in the 80's (Desplatz, Jamet, Passeron, and Romans, 2003), which was stronger for more educated workers (as seen in the first specification), was also higher for less experienced workers. They probably have less bargaining power as they are more likely to be unemployed (see Figure 13 (b) in the appendix). This could entail a stronger decrease in between- and within-education group wage inequalities for the low levels of experience.

Furthermore, the increase in minimum wage could affect the wages of workers until higher levels of education for the lower levels of experience, entailing a stronger decrease in between-education group wage inequalities for the less experienced workers.

As between-education decreased, education premiums decreased all over the period, strongly for the less experienced workers. This can be partly due to a cohort effect linked to a supply/demand effect:



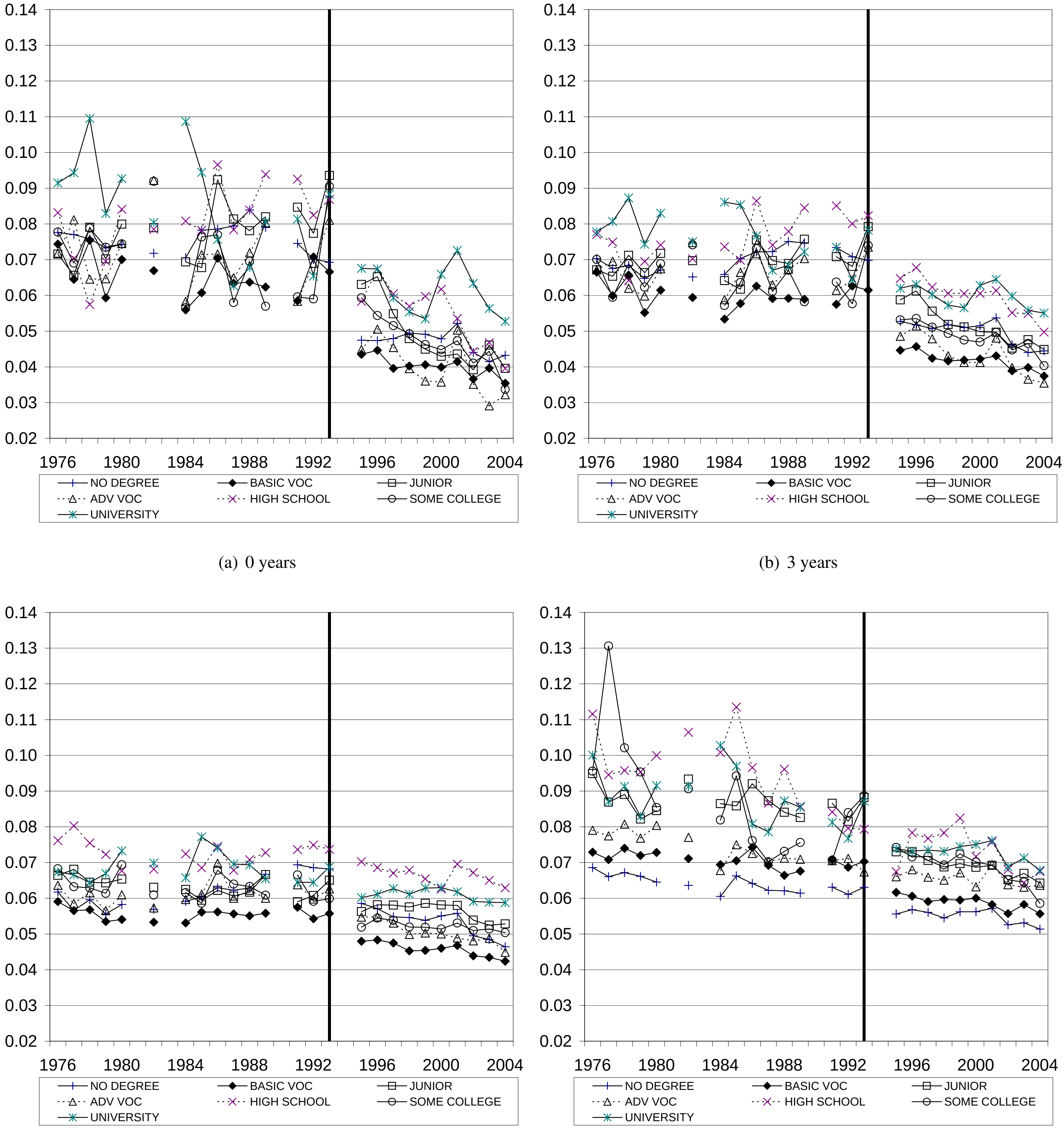
(a) 0 years

(b) 3 years

(c) 10 years

(d) 30 years

Figure 10: Model (4): Q90-Q10 log wage differences adjusted for various levels of experience.



(a) 0 years

(b) 3 years

(c) 10 years

(d) 30 years

Figure 11: Model (4): Gini coefficients of log wage distributions adjusted for various levels of experience.

as the less experienced workers are more and more educated, the education premiums diminish – for example due to over-education, if the demand for more educated workers did not increase as much.

Note that, as it is well-documented in the literature, the decreasing returns to education are partly compensated by a lower unemployment and a higher probability to accumulate experience for educated people.

7 Sensitivity analysis

In this section, we present several alternatives to check the sensitivity of our results: including student working periods, considering only the experience accumulated once studies completed, considering only the 15-54 years old workers, including part-time workers. The results presented for both specifications remain.[16]

- *Including student working periods*
  The leaving school year is imputed for one third of the sample. This imputation may affect the results because it determines whether some observations are included in the sample as student working periods are excluded. To check the sensitivity of our results to this step, we consider an alternative specification, in which the education variable contains an additional category "in studies" for students. The specification is estimated on the whole sample. The within- and between-inequalities and their evolutions do not change when student working periods are included.
- *Valuating only experience after schooling*
  We did not make differences between experience accumulated when working during the studies and experience accumulated after the end of the studies. In this alternative, we check that the results are the same as those presented previously when only experience accumulated after the end of the studies is considered.
- *Considering only the 15-54 year old workers*
  Pension reforms, pre-retirement schemes, increasing senior unemployment could drive a part of our results. We run the two specifications on a restricted sample with only the 15-54 year old workers. Results are the same as before.
- *Including part-time working periods*
  We consider an extended sample with full-time and part-time working periods and, we include a dummy variable "part-time working period" in both specifications. Our results remain.

[16]Results are available upon request.

8 Concluding comments

In this paper, we analysed the evolutions of the male full-time wage inequalities in the French private sector from 1976 to 2004. We applied quantile regression to Mincer-type equations to disentangle between- and within-education group wage inequalities adjusted for experience, and we separately described their evolutions. We also considered an alternative specification, where education and experience are interacted. This latter accounts for a potential non-separability of the two types of human capital and allows us to stress education group wage inequalities evolutions at different levels of experience. We find several results. (1) The overall wage inequality was stable from 1976 to 1992 and slightly decreased from 1995 to 2004. (2) The within-education group wage inequalities increase with education and are higher across non-vocational degrees than vocational ones. (3) The between-education group wage inequalities increase with experience. (4) The between-education group wage inequalities decreased all over the period, due to decreasing education premiums, particularly for low levels of experience. (5) The within-education group wage inequalities were rather stable from 1976 to 1992 and decreased between 1995 and 2004, strongly for low levels of experience.

Unemployment evolution and mininum wage rise may largely explain the changes in wage inequalities by education between 1976 and 2004. Unemployment increase may have induced the 1980's wage moderation, more strongly on the wages of the more educated and the less experienced, and on the top wages within each education group. The minimum wage increase could have entailed both a decrease in between- and within-education group wage inequalities over time through a tightening of the bottom of the distribution between and within education groups. Supply/demand effects may have also played a role, as older cohorts have been gradually replaced by more educated ones. Institutional explanations are consistent with the divergent trends observed in France and in the US.

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A Data construction

The data come from the match between the DADS panel (déclarations annuelles de données sociales) and the EDP database (échantillon démographique permanent).Those two databases and the matched one are produced and maintained by the INSEE (French National Institute of Statistics and Economic Studies). The DADS panel is a special exploitation for scientific analysis of the DADS, an exhaustive administrative database of employer-employee wage-bill information, annually and compulsory filled in by any firm establishment.The DADS panel contains information on all wages paid to, all working periods of, and all private sector employers of wage-earners born in October of even years. Education information is extracted from the EDP database. The EDP database collects census information (education, family status at the census dates, ...) and civil state administrative information (date of marriage, child birth, ...) of individuals born one of the four first days of October. The birth date correspondence allows to match both databases on individuals born in France one of the four first days of October of even years and who worked at least once in the private sector. For people born abroad, the matching is not possible. In the following, we detail the construction of variables needed in the analysis.

A.1 School-leaving age and school-leaving year

The school-leaving age and the school-leaving year are required to determine whether a work period occurred before an individual finished his/her studies or after. School-leaving age and school-leaving year are collected in the 1968, 1975 and 1982 censuses. The question was suppressed afterwards. When the data is available, we do the following corrections. Ages below the legal minimum school-leaving age, which depends on the birth year, are corrected to that legal minimum. When different ages are reported in different censuses, we choose the one reported in the oldest census (occurring after the end of schooling) when it is strictly superior to the legal minimum age, with in mind the idea to minimize potential memory bias. The school-leaving age/year are available for the two thirds of the sample. The question was suppressed in the 1990 and 1999 censuses and the annual census surveys 2004-2006. In those censuses, individuals were asked to indicate whether they were currently students or not. Consequently, for those who had not finished their studies in 1982 and those who had not responded to the question previously to 1990, the exact school-leaving age/year are unknown. For those, we impute school-leaving ages by exploiting the empirical distributions of school-leaving age conditional on birth cohort, sex, and degree, which we constructed by using the French Labor Force surveys (LFS).[17]

A.2 Education variable

We use the EDP information to construct the highest degree obtained once studies completed. We follow Abowd, Kramarz, and Margolis (1999) to recode the degree. The degree categories used are reported in Table 1 with their shares in the panel population. As for the school-leaving age, the information on the degree may differ between censuses. We choose the one corresponding to the census that follows the end of studies – as predicted by the school-leaving year variable presented above – or when the person has just passed 27. The idea is again to minimize potential memory bias. When no degree are declared in that census or when the information is not precise enough to determine the education category, we

[17]To avoid memory bias, for each cohort, we consider LFS surveys when individuals are between 35 and 40.

use the information reported in the following ones.[18] Individuals with missing information are excluded from the analysis.

A.3 Experience variable

The experience variable refers to the experience accumulated as a wage-earner in the private sector. Its construction is mainly based on the exhaustive nature of DADS panel information. The experience variable sums up the shares of working days per year since the first occurrence in the panel up to the current working period. To construct the experience variable, we also use the information in the 1967-1975 DADS panel, which is only available for a fraction of people. For those who are present in the DADS in 1976 or before with a school-leaving year anterior to the year of first appearance, we consider the difference between the year of the panel first appearance and the school-leaving year as complete years of experience. In other words, we assume those individuals were employed between the end of their studies and their first occurrence in the panel. We argue this is not a strong assumption because the unemployment and part-time work were not frequent in the 60's-70's, especially for men. Furthermore, the DADS data is missing for 1981, 1983 and 1990. So, we correct the experience variables for these three years to take into account the missing part of experience accumulated during 1981, 1983 and/or 1990. We average the shares of working days per year for the year just before and for the year just after the missing year and we add this average to the experience variables for the following years.

B Adjusted Gini coefficient

Let Y be a positive r.v., with distribution function $F(y) = P[Y \leq y]$ and $E(Y) = \mu$. The quantile function is defined as

$$\begin{aligned} \theta :\rightarrow q_Y &= inf\{y|P[Y \leq y] \geq \theta\} \\ &= F^{-1}(\theta) \end{aligned}$$

when F is invertible. In the quantile regression model , $q_Y(\theta|x) = x'\beta(\theta)$.
We want to approximate the Gini coefficient of $Y|x$. Using the Lorenz curve, the Gini coefficient is equal to :

$$G(Y|x) = 1 - 2\int_0^1 L_Y(\theta|x)d\theta$$

[18]In the 1968 and the 1990 censuses, general high school and vocational high school are not distinguished. The same occurs for "brevet de technicien" (a vocational high school degree) and BTS (a post-Bac vocational degree) in the 1968 census. In the 1968 and the 1975 censuses, there is no distinction between college and university degrees. In such cases, we use the following census information when available and choose the most frequent category in the population otherwise.

The Lorenz curve can be written using the quantile function:

$$L_Y(\theta|x) = \frac{1}{\mu_x}\int_0^\theta q_Y(t|x)dt$$

where $\mu_x = E(Y|x)$.
Using the quantile model (see Koenker (2005)), it follows that

$$L_Y(\theta|x) = \frac{1}{\mu_x}\int_0^\theta x'\beta(t)dt$$

The Gini of the conditional distribution is then :

$$G(Y|x) = 1 - \frac{2}{\mu_x}\int_0^1\int_0^\theta x'\beta(t)dtd\theta$$

after an integration by parts with $u = \int_0^\theta x'\beta(t)dt$ and $v = \theta$

$$\begin{aligned} G(Y|x) &= 1 - \frac{2}{\mu_x}\int_0^1 x'\beta(\theta)(1-\theta)d\theta \\ &= 1 - \frac{2}{\int_0^1 x'\beta(\theta)d\theta}\int_0^1 x'\beta(\theta)(1-\theta)d\theta \\ &= 2\frac{\int_0^1 x'\beta(\theta)\theta d\theta}{\int_0^1 x'\beta(\theta)d\theta} - 1 \end{aligned}$$

as $\mu_x = \int_0^1 x'\beta(\theta)d\theta$.[19]

Quantile regressions give estimates $\hat{q}_Y(\theta_1), \ldots, \hat{q}_Y(\theta_{K-1})$ of quantiles at orders $\theta_1, \ldots, \theta_{K-1}$. We approximate $q_Y(\theta_0)$ and $q_Y(\theta_K)$ by extrapolating the slope from the first two and the last two available quantiles.

To approximate G, we approximate each integral by the trapezoidal rule using intervals of size $1/K$. It follows that :

$$\begin{aligned} \int_0^1 x'\beta(\theta)\theta d\theta &\approx \sum_{k=1}^{K}\frac{\theta_{\frac{k}{K}} - \theta_{\frac{k-1}{K}}}{2}\left(x'\hat{\beta}\left(\frac{k}{K}\right)\frac{k}{K} + x'\hat{\beta}\left(\frac{k-1}{K}\right)\left(\frac{k-1}{K}\right)\right) \\ &\approx \frac{1}{2K}\left(2\sum_{k=1}^{K-1}x'\hat{\beta}\left(\frac{k}{K}\right)\frac{k}{K} + x'\hat{\beta}(1)\right) \end{aligned}$$

[19] $\mu_x = \int_0^{+\infty} f(y|x)ydy = \int_0^1 f(F^{-1}(\theta|x))F^{-1}(\theta|x)/f(F^{-1}(\theta|x))d\theta = \int_0^1 F^{-1}(\theta|x)d\theta = \int_0^1 q_Y(\theta|x)d\theta$ and using the quantile regression model, $\mu_x = \int_0^1 x'\beta(\theta)d\theta$.

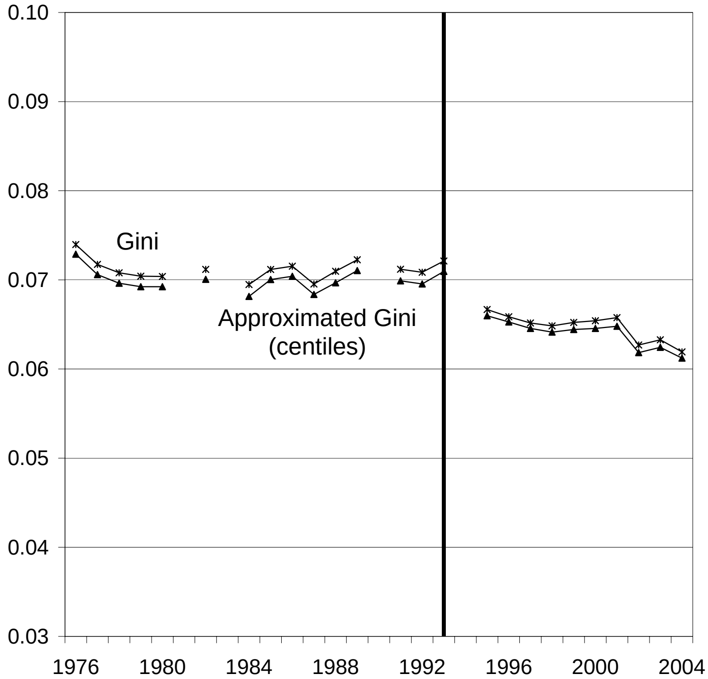


Figure 12: Gini coefficient of the log daily wage

and

$$\int_0^1 x'\beta(\theta)d\theta \approx \sum_{k=1}^{K} \frac{\theta_{\frac{k}{K}} - \theta_{\frac{k-1}{K}}}{2} \left(x'\hat{\beta}\left(\frac{k}{K}\right) + x'\hat{\beta}\left(\frac{k-1}{K}\right)\right)$$
$$\approx \frac{1}{2K}\left(x'\hat{\beta}(0) + 2\sum_{k=1}^{K-1} x'\hat{\beta}\left(\frac{k}{K}\right) + x'\hat{\beta}(1)\right)$$

then

$$G(Y|x) \approx 2\frac{2\sum_{k=1}^{K-1} x'\hat{\beta}\left(\frac{k}{K}\right)\frac{k}{K} + x'\hat{\beta}(1)}{x'\hat{\beta}(0) + 2\sum_{k=1}^{K-1} x'\hat{\beta}\left(\frac{k}{K}\right) + x'\hat{\beta}(1)} - 1 \quad (5)$$

To assess the accuracy of the method, we report on Figure 12 the Gini coefficient of the whole unconditional distribution and the one approximated using centiles (equation (5)). They are similar.

C Additionnal results

Table 2: Model (2): QR estimates (1).

	1976	1980	1984	1988	1992	1996	2000	2004
(Intercept)	3.227***	3.288***	3.325***	3.332***	3.393***	3.320***	3.320***	3.377***
ols	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.009)
(Intercept)	2.942***	2.994***	3.081***	3.027***	3.110***	3.091***	3.125***	3.214***
0.1	(0.020)	(0.013)	(0.015)	(0.016)	(0.017)	(0.015)	(0.018)	(0.017)
(Intercept)	3.130***	3.162***	3.212***	3.246***	3.297***	3.203***	3.249***	3.311***
0.25	(0.010)	(0.008)	(0.008)	(0.010)	(0.008)	(0.008)	(0.011)	(0.008)
(Intercept)	3.281***	3.307***	3.342***	3.378***	3.427***	3.333***	3.358***	3.411***
0.5	(0.007)	(0.007)	(0.009)	(0.008)	(0.008)	(0.009)	(0.008)	(0.009)
(Intercept)	3.440***	3.458***	3.491***	3.542***	3.596***	3.489***	3.472***	3.538***
0.75	(0.010)	(0.009)	(0.008)	(0.011)	(0.010)	(0.014)	(0.010)	(0.011)
(Intercept)	3.621***	3.695***	3.694***	3.735***	3.812***	3.659***	3.625***	3.686***
0.9	(0.012)	(0.011)	(0.019)	(0.018)	(0.019)	(0.019)	(0.013)	(0.019)
dip3	0.379***	0.347***	0.319***	0.309***	0.304***	0.278***	0.273***	0.228***
ols	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.008)	(0.008)	(0.008)
dip3	0.202***	0.199***	0.172***	0.190***	0.185***	0.156***	0.149***	0.114***
0.1	(0.027)	(0.016)	(0.017)	(0.017)	(0.018)	(0.013)	(0.011)	(0.010)
dip3	0.277***	0.258***	0.219***	0.202***	0.201***	0.192***	0.177***	0.139***
0.25	(0.015)	(0.013)	(0.009)	(0.010)	(0.011)	(0.010)	(0.010)	(0.011)
dip3	0.359***	0.314***	0.295***	0.270***	0.257***	0.241***	0.227***	0.182***
0.5	(0.012)	(0.013)	(0.012)	(0.009)	(0.013)	(0.011)	(0.009)	(0.007)
dip3	0.440***	0.417***	0.382***	0.350***	0.337***	0.327***	0.310***	0.255***
0.75	(0.020)	(0.017)	(0.017)	(0.018)	(0.012)	(0.015)	(0.011)	(0.015)
dip3	0.536***	0.480***	0.468***	0.423***	0.425***	0.405***	0.385***	0.331***
0.9	(0.018)	(0.020)	(0.022)	(0.022)	(0.021)	(0.023)	(0.025)	(0.025)
dip4	0.165***	0.148***	0.140***	0.141***	0.149***	0.132***	0.127***	0.117***
ols	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)
dip4	0.115***	0.104***	0.108***	0.115***	0.135***	0.115***	0.104***	0.088***
0.1	(0.008)	(0.009)	(0.008)	(0.009)	(0.009)	(0.008)	(0.007)	(0.006)
dip4	0.128***	0.119***	0.113***	0.110***	0.124***	0.114***	0.108***	0.093***
0.25	(0.005)	(0.007)	(0.005)	(0.005)	(0.007)	(0.006)	(0.004)	(0.005)
dip4	0.160***	0.146***	0.131***	0.132***	0.132***	0.121***	0.114***	0.105***
0.5	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)
dip4	0.181***	0.167***	0.152***	0.144***	0.143***	0.127***	0.127***	0.112***
0.75	(0.008)	(0.006)	(0.005)	(0.008)	(0.007)	(0.006)	(0.006)	(0.006)
dip4	0.183***	0.163***	0.150***	0.140***	0.151***	0.128***	0.112***	0.111***
0.9	(0.009)	(0.009)	(0.011)	(0.010)	(0.011)	(0.011)	(0.010)	(0.010)
dip5	0.470***	0.442***	0.433***	0.430***	0.420***	0.374***	0.348***	0.305***
ols	(0.011)	(0.010)	(0.010)	(0.011)	(0.010)	(0.008)	(0.008)	(0.007)
dip5	0.334***	0.282***	0.281***	0.289***	0.301***	0.261***	0.263***	0.210***
0.1	(0.017)	(0.016)	(0.017)	(0.018)	(0.020)	(0.014)	(0.009)	(0.011)
dip5	0.397***	0.370***	0.381***	0.342***	0.340***	0.306***	0.275***	0.234***
0.25	(0.013)	(0.017)	(0.013)	(0.010)	(0.012)	(0.011)	(0.007)	(0.006)
dip5	0.483***	0.457***	0.440***	0.424***	0.406***	0.345***	0.309***	0.270***
0.5	(0.012)	(0.014)	(0.015)	(0.013)	(0.010)	(0.009)	(0.009)	(0.008)
dip5	0.526***	0.508***	0.490***	0.481***	0.465***	0.405***	0.359***	0.297***
0.75	(0.017)	(0.011)	(0.013)	(0.016)	(0.013)	(0.013)	(0.010)	(0.010)
dip5	0.523***	0.528***	0.498***	0.510***	0.515***	0.440***	0.361***	0.327***
0.9	(0.017)	(0.027)	(0.026)	(0.027)	(0.022)	(0.019)	(0.016)	(0.016)
dip6	0.629***	0.561***	0.544***	0.552***	0.555***	0.488***	0.483***	0.457***
ols	(0.014)	(0.012)	(0.012)	(0.012)	(0.012)	(0.011)	(0.010)	(0.010)
dip6	0.348***	0.321***	0.315***	0.330***	0.361***	0.271***	0.270***	0.233***
0.1	(0.031)	(0.030)	(0.026)	(0.022)	(0.017)	(0.020)	(0.013)	(0.019)
dip6	0.469***	0.425***	0.423***	0.398***	0.403***	0.360***	0.334***	0.281***
0.25	(0.020)	(0.021)	(0.015)	(0.016)	(0.017)	(0.014)	(0.013)	(0.012)
dip6	0.623***	0.550***	0.528***	0.533***	0.533***	0.470***	0.442***	0.399***
0.5	(0.022)	(0.014)	(0.017)	(0.014)	(0.022)	(0.019)	(0.022)	(0.013)
dip6	0.768***	0.680***	0.661***	0.671***	0.640***	0.579***	0.569***	0.534***
0.75	(0.026)	(0.018)	(0.026)	(0.022)	(0.019)	(0.019)	(0.014)	(0.021)
dip6	0.906***	0.793***	0.794***	0.773***	0.771***	0.676***	0.673***	0.652***
0.9	(0.035)	(0.027)	(0.030)	(0.036)	(0.029)	(0.041)	(0.027)	(0.039)

to be continued

Table 3: Model (2): QR estimates (2).

	1976	1980	1984	1988	1992	1996	2000	2004
dip7	0.727***	0.645***	0.633***	0.622***	0.623***	0.575***	0.557***	0.504***
ols	(0.016)	(0.013)	(0.012)	(0.011)	(0.010)	(0.008)	(0.007)	(0.007)
dip7	0.532***	0.439***	0.482***	0.505***	0.489***	0.426***	0.420***	0.349***
0.1	(0.053)	(0.029)	(0.030)	(0.019)	(0.017)	(0.015)	(0.012)	(0.010)
dip7	0.621***	0.572***	0.570***	0.521***	0.539***	0.498***	0.468***	0.403***
0.25	(0.018)	(0.020)	(0.013)	(0.011)	(0.010)	(0.009)	(0.007)	(0.007)
dip7	0.715***	0.641***	0.606***	0.591***	0.589***	0.546***	0.513***	0.463***
0.5	(0.017)	(0.014)	(0.011)	(0.012)	(0.011)	(0.009)	(0.007)	(0.006)
dip7	0.800***	0.724***	0.695***	0.676***	0.660***	0.615***	0.573***	0.527***
0.75	(0.030)	(0.018)	(0.017)	(0.017)	(0.016)	(0.011)	(0.009)	(0.010)
dip7	0.900***	0.784***	0.766***	0.757***	0.720***	0.675***	0.632***	0.587***
0.9	(0.023)	(0.033)	(0.030)	(0.023)	(0.020)	(0.021)	(0.017)	(0.017)
dip8	1.128***	1.028***	1.018***	1.058***	1.063***	0.977***	0.970***	0.926***
ols	(0.014)	(0.012)	(0.012)	(0.012)	(0.011)	(0.009)	(0.008)	(0.008)
dip8	0.712***	0.638***	0.626***	0.738***	0.786***	0.701***	0.665***	0.615***
0.1	(0.057)	(0.054)	(0.060)	(0.035)	(0.023)	(0.026)	(0.017)	(0.020)
dip8	1.074***	0.968***	0.956***	0.984***	0.976***	0.883***	0.853***	0.792***
0.25	(0.025)	(0.020)	(0.024)	(0.020)	(0.015)	(0.015)	(0.011)	(0.014)
dip8	1.191***	1.126***	1.095***	1.093***	1.061***	0.982***	0.957***	0.910***
0.5	(0.017)	(0.021)	(0.015)	(0.013)	(0.011)	(0.009)	(0.011)	(0.013)
dip8	1.246***	1.195***	1.183***	1.185***	1.141***	1.072***	1.051***	1.013***
0.75	(0.020)	(0.018)	(0.014)	(0.020)	(0.019)	(0.013)	(0.014)	(0.012)
dip8	1.318***	1.198***	1.273***	1.258***	1.215***	1.137***	1.161***	1.087***
0.9	(0.030)	(0.030)	(0.033)	(0.025)	(0.024)	(0.024)	(0.022)	(0.021)
exper	7.547***	7.050***	5.939***	6.181***	5.345***	6.487***	6.642***	5.875***
ols	(0.167)	(0.160)	(0.173)	(0.180)	(0.176)	(0.164)	(0.162)	(0.168)
exper	6.832***	6.943***	5.087***	6.297***	4.864***	5.529***	5.499***	4.889***
0.1	(0.331)	(0.185)	(0.213)	(0.291)	(0.271)	(0.236)	(0.329)	(0.291)
exper	6.710***	6.654***	5.180***	5.190***	4.431***	5.792***	5.273***	4.879***
0.25	(0.186)	(0.152)	(0.145)	(0.179)	(0.137)	(0.137)	(0.193)	(0.166)
exper	6.773***	6.653***	5.573***	5.319***	4.909***	5.955***	5.900***	5.151***
0.5	(0.161)	(0.146)	(0.166)	(0.173)	(0.185)	(0.233)	(0.157)	(0.209)
exper	7.101***	7.119***	5.810***	5.538***	5.032***	6.311***	6.773***	5.493***
0.75	(0.196)	(0.183)	(0.168)	(0.240)	(0.253)	(0.293)	(0.224)	(0.254)
exper	7.350***	6.259***	5.790***	6.211***	5.355***	7.231***	7.963***	6.147***
0.9	(0.297)	(0.271)	(0.383)	(0.368)	(0.441)	(0.442)	(0.315)	(0.409)
exper2	−23.675***	−21.590***	−15.996***	−16.591***	−13.413***	−19.544***	−19.517***	−16.684***
ols	(0.835)	(0.842)	(0.947)	(1.014)	(1.010)	(0.953)	(0.955)	(0.985)
exper2	−24.471***	−25.113***	−16.937***	−21.124***	−14.662***	−19.120***	−19.082***	−17.557***
0.1	(1.556)	(1.002)	(1.133)	(1.628)	(1.516)	(1.299)	(1.796)	(1.464)
exper2	−22.908***	−22.308***	−14.898***	−14.545***	−11.326***	−18.747***	−15.645***	−15.183***
0.25	(0.982)	(0.860)	(0.855)	(0.979)	(0.785)	(0.810)	(1.096)	(0.996)
exper2	−21.204***	−20.192***	−14.496***	−13.369***	−12.326***	−17.270***	−16.772***	−13.875***
0.5	(0.869)	(0.804)	(0.925)	(0.992)	(1.101)	(1.480)	(1.043)	(1.280)
exper2	−20.607***	−21.056***	−13.476***	−12.313***	−10.858***	−17.642***	−18.942***	−12.867***
0.75	(0.979)	(1.128)	(1.026)	(1.418)	(1.609)	(1.734)	(1.346)	(1.720)
exper2	−18.858***	−14.507***	−11.886***	−14.621***	−11.946***	−20.768***	−23.755***	−13.692***
0.9	(1.706)	(1.678)	(2.395)	(2.061)	(2.551)	(2.665)	(2.031)	(2.377)
exper3	22.526***	20.554***	13.099***	13.850***	10.484***	20.570***	19.969***	18.261***
ols	(1.177)	(1.246)	(1.465)	(1.604)	(1.614)	(1.567)	(1.600)	(1.653)
exper3	25.396***	26.745***	17.260***	22.142***	13.401***	21.745***	22.367***	22.287***
0.1	(2.107)	(1.598)	(1.765)	(2.506)	(2.436)	(2.160)	(2.911)	(2.179)
exper3	22.942***	22.512***	12.557***	12.061***	8.281***	20.388***	15.886***	17.213***
0.25	(1.432)	(1.330)	(1.380)	(1.533)	(1.225)	(1.349)	(1.786)	(1.745)
exper3	19.877***	18.748***	10.786***	9.831***	9.469***	17.145***	16.572***	14.045***
0.5	(1.255)	(1.229)	(1.439)	(1.522)	(1.771)	(2.524)	(1.902)	(2.185)
exper3	18.453***	20.228***	8.582***	7.688***	7.000**	17.998***	19.127***	11.654***
0.75	(1.385)	(1.907)	(1.700)	(2.314)	(2.828)	(2.854)	(2.260)	(3.157)
exper3	14.873***	10.705***	7.224*	11.768***	9.548**	22.982***	27.209***	12.741***
0.9	(2.692)	(2.750)	(4.067)	(3.384)	(4.037)	(4.445)	(3.655)	(3.922)
Joint F-test	35.4***	35.9***	39.1***	29.7***	31.6***	34.7***	49.6***	49.7***

***: p-value$<$ .01, **: p-value$<$ .05, *: p-value$<$ .1. Bootstrapped standard errors obtained with 50 replicates are reported in parentheses.

Table 4: Model (2): tests for location-shift and location-scale-shift models.

	1976	1980	1984	1988	1992	1996	2000	2004
				Tests for a location-shift model H_{01}				
F-stat for Wald test of joint H_01 (1)	35.4***	35.9***	39.1***	29.7***	31.6***	34.7***	49.6***	49.7***
F-stat for Wald test of univariate subhypotheses (1)								
dip3	41.6***	40.8***	46.5***	28.6***	34.8***	35.8***	30.1***	21.4***
dip4	16.0***	15.2***	8.5***	7.1***	2.8**	1.1	2.9**	3.0**
dip5	22.8***	35.2***	23.4***	28.7***	24.9***	25.0***	18.2***	15.6***
dip6	47.8***	68.9***	60.8***	51.0***	51.9***	41.2***	80.5***	51.7***
dip7	45.0***	21.4***	18.1***	29.7***	28.6***	39.9***	39.9***	60.2***
dip8	25.2***	31.0***	54.2***	48.7***	50.5***	56.7***	113.0***	106.5***
exper	1.6	5.4***	2.8**	7.6***	4.3***	4.1***	17.1***	2.8**
exper2	2.3*	9.2***	1.6	9.9***	2.6**	1.4	5.4***	2.4**
exper3	3.7***	8.8***	3.2**	11.6***	2.4*	1.8	4.9***	4.4***
Khmaladze stat for joint H_{01} (2)	23.2***	30.7***	44.8***	62.2***	45.2***	44.8***	61.5***	41.4***
Khmaladze stat for univariate subhypotheses (2)								
dip3	2.2**	5.8***	4.0***	4.2***	4.0***	2.5**	3.1***	2.7***
dip4	2.5**	1.8	2.2**	1.8	0.8	1.9*	1.4	1.7
dip5	2.6**	2.2**	3.8***	3.0***	2.5**	4.3***	2.8***	4.5***
dip6	7.5***	3.2***	1.8	6.1***	3.9***	6.2***	6.3***	2.0*
dip7	2.2**	3.0***	2.6**	2.2**	3.4***	4.3***	5.0***	3.6***
dip8	3.5***	7.2***	3.7***	3.7***	5.0***	5.4***	3.4***	7.0***
exper	1.1	1.5	0.6	1.7	1.8	1.0	1.2	0.8
exper2	0.6	0.6	1.5	0.7	0.5	1.7	1.1	0.5
exper3	0.7	0.6	1.7	0.9	0.5	1.7	1.3	0.4
				Tests for a location-scale-shift model H_{02}				
Khmaladze stat for joint H_{02} (2)	7.4	12.7***	11.9***	8.3	5.3	7.8	6.4	7.2
Khmaladze stat for univariate subhypotheses (2)								
dip3	0.8	0.9	0.4	0.5	0.4	0.3	0.5	0.9
dip4	1.6	2.5**	1.6	1.8	0.5	0.6	1.7	0.9
dip5	2.4**	2.0*	1.3	1.3	1.2	0.7	0.9	0.5
dip6	1.4	0.8	0.5	1.4	0.8	0.5	0.5	0.3
dip7	0.5	0.9	0.9	0.8	1.2	0.2	0.3	1.0
dip8	1.4	4.5***	2.4**	1.0	0.7	1.4	1.0	1.7
exper	1.0	1.7	0.9	0.4	0.7	0.7	0.8	0.6
exper2	0.7	1.3	0.7	0.7	0.6	0.9	0.7	0.4
exper3	0.6	1.0	0.5	0.8	0.6	0.9	0.7	0.3

***: p-value$<.01$, **: p-value$<.05$, *: p-value$<.1$.

(1) Wald tests for equal quantiles parameters at order .1, .25, .5, .75 and .9, see Koenker and Bassett (1982). F-stat are reported.

(2) To construct Koenker and Xiao (2002) tests for H_{01} and H_{02}, quantile regressions were performed at orders .1 to .9 by .05 increase. The critical values used are those reported in Table B.1. and B.2. p 318 in Koenker (2005).

Quantile regressions and tests were performed in R with the quantile regression package `quantreg`, see Koenker (2005).

Table 5: Model (4): QR estimates (1).

	1976	1980	1984	1988	1992	1996	2000	2004
(Intercept)	3.348***	3.471***	3.473***	3.477***	3.553***	3.579***	3.564***	3.593***
ols	(0.015)	(0.014)	(0.016)	(0.017)	(0.016)	(0.016)	(0.017)	(0.018)
(Intercept)	3.017***	3.091***	3.092***	3.004***	3.176***	3.353***	3.267***	3.354***
0.1	(0.031)	(0.025)	(0.035)	(0.046)	(0.046)	(0.021)	(0.045)	(0.021)
(Intercept)	3.225***	3.284***	3.332***	3.365***	3.432***	3.432***	3.440***	3.478***
0.25	(0.012)	(0.010)	(0.014)	(0.014)	(0.011)	(0.012)	(0.013)	(0.015)
(Intercept)	3.409***	3.459***	3.486***	3.518***	3.554***	3.544***	3.569***	3.598***
0.5 vspace-.01cm	(0.010)	(0.011)	(0.015)	(0.013)	(0.011)	(0.011)	(0.017)	(0.015)
(Intercept)	3.566***	3.657***	3.650***	3.698***	3.733***	3.687***	3.703***	3.729***
0.75	(0.012)	(0.018)	(0.014)	(0.019)	(0.019)	(0.020)	(0.018)	(0.016)
(Intercept)	3.727***	3.883***	3.874***	3.909***	3.969***	3.873***	3.821***	3.860***
0.9	(0.020)	(0.026)	(0.033)	(0.047)	(0.041)	(0.043)	(0.035)	(0.032)
dip3	0.113***	0.034	0.054*	0.105***	0.066**	0.049	0.038	0.047
ols	(0.033)	(0.031)	(0.033)	(0.034)	(0.033)	(0.033)	(0.034)	(0.035)
dip3	0.018	0.038	0.157***	0.157	0.084	−0.050	0.124**	0.027
0.1	(0.069)	(0.053)	(0.050)	(0.098)	(0.068)	(0.043)	(0.058)	(0.035)
dip3	0.073***	−0.000	0.033	0.034	−0.032	−0.060**	0.022	0.031
0.25	(0.027)	(0.035)	(0.023)	(0.037)	(0.033)	(0.029)	(0.027)	(0.039)
dip3	0.062**	0.026	0.018	0.060*	0.048*	−0.001	−0.002	0.038
0.5	(0.029)	(0.035)	(0.025)	(0.032)	(0.028)	(0.021)	(0.030)	(0.035)
dip3	0.099***	0.003	0.085***	0.087**	0.113**	0.129**	0.008	0.001
0.75	(0.033)	(0.048)	(0.027)	(0.044)	(0.044)	(0.059)	(0.046)	(0.035)
dip3	0.123**	0.079	0.030	0.156**	0.178*	0.242**	0.056	0.093
0.9	(0.056)	(0.066)	(0.068)	(0.075)	(0.100)	(0.101)	(0.070)	(0.081)
dip4	0.057***	−0.032*	0.038*	0.051**	0.033	−0.007	0.010	0.047**
ols	(0.020)	(0.019)	(0.020)	(0.022)	(0.020)	(0.021)	(0.022)	(0.022)
dip4	0.005	−0.009	0.151***	0.234***	0.149***	−0.024	0.092*	0.078**
0.1	(0.042)	(0.029)	(0.038)	(0.050)	(0.052)	(0.022)	(0.047)	(0.032)
dip4	0.041**	0.011	0.033**	0.043**	0.042***	−0.008	0.023	0.041**
0.25	(0.017)	(0.016)	(0.016)	(0.017)	(0.013)	(0.017)	(0.020)	(0.019)
dip4	0.041***	0.000	0.010	0.038**	0.062***	0.007	0.006	0.022
0.5	(0.014)	(0.016)	(0.021)	(0.016)	(0.014)	(0.018)	(0.018)	(0.022)
dip4	0.061***	−0.047**	0.008	0.002	0.035	0.002	−0.024	0.023
0.75	(0.018)	(0.020)	(0.019)	(0.022)	(0.025)	(0.023)	(0.022)	(0.021)
dip4	0.055*	−0.050	−0.026	−0.006	0.013	−0.028	−0.037	0.030
0.9	(0.028)	(0.035)	(0.034)	(0.053)	(0.050)	(0.053)	(0.044)	(0.044)
dip5	0.294***	0.144***	0.152***	0.132***	0.135***	−0.052*	0.031	0.047*
ols	(0.040)	(0.037)	(0.038)	(0.040)	(0.035)	(0.028)	(0.027)	(0.027)
dip5	0.198***	0.165***	0.220***	0.307***	0.202***	−0.121**	0.133**	0.072**
0.1	(0.059)	(0.055)	(0.054)	(0.074)	(0.059)	(0.058)	(0.057)	(0.029)
dip5	0.214***	0.086**	0.108***	0.078**	0.129***	−0.037	0.043**	0.040*
0.25	(0.036)	(0.036)	(0.040)	(0.034)	(0.026)	(0.028)	(0.021)	(0.021)
dip5	0.247***	0.136***	0.139***	0.070**	0.121***	−0.020	0.028	0.037
0.5	(0.044)	(0.043)	(0.032)	(0.033)	(0.027)	(0.022)	(0.027)	(0.027)
dip5	0.289***	0.158***	0.153***	0.117**	0.089**	−0.053	−0.008	0.027
0.75	(0.043)	(0.043)	(0.039)	(0.058)	(0.043)	(0.040)	(0.026)	(0.032)
dip5	0.287***	0.158*	0.114	0.111	0.145	−0.074	−0.031	0.025
0.9	(0.076)	(0.095)	(0.077)	(0.101)	(0.093)	(0.055)	(0.056)	(0.046)
dip6	0.279***	0.124***	0.226***	0.284***	0.288***	0.092**	0.095**	0.023
ols	(0.044)	(0.038)	(0.043)	(0.045)	(0.047)	(0.039)	(0.041)	(0.039)
dip6	0.256***	0.087	0.132	0.262***	0.256***	−0.039	0.051	0.063
0.1	(0.070)	(0.074)	(0.081)	(0.091)	(0.073)	(0.073)	(0.069)	(0.044)
dip6	0.227***	0.071	0.170***	0.201***	0.139***	−0.009	0.005	0.020
0.25	(0.044)	(0.048)	(0.048)	(0.057)	(0.046)	(0.034)	(0.036)	(0.038)
dip6	0.280***	0.092**	0.251***	0.233***	0.172***	0.017	−0.009	−0.031
0.5	(0.046)	(0.042)	(0.054)	(0.061)	(0.050)	(0.048)	(0.058)	(0.042)
dip6	0.258***	0.115**	0.317***	0.338***	0.327***	0.144***	0.059	−0.023
0.75	(0.051)	(0.048)	(0.043)	(0.075)	(0.089)	(0.054)	(0.068)	(0.073)
dip6	0.272***	0.178*	0.339***	0.385***	0.576***	0.390***	0.409***	0.068
0.9	(0.091)	(0.099)	(0.096)	(0.104)	(0.111)	(0.100)	(0.124)	(0.107)

to be continued

Table 6: Model (4): QR estimates (2).

	1976	1980	1984	1988	1992	1996	2000	2004
dip7	0.456***	0.302***	0.339***	0.289***	0.284***	0.045	0.135***	0.135***
ols	(0.045)	(0.038)	(0.038)	(0.036)	(0.032)	(0.028)	(0.028)	(0.029)
dip7	0.327***	0.178**	0.355***	0.431***	0.285***	−0.055	0.150***	0.159***
0.1	(0.101)	(0.071)	(0.072)	(0.060)	(0.066)	(0.042)	(0.056)	(0.037)
dip7	0.366***	0.264***	0.319***	0.283***	0.243***	0.012	0.130***	0.146***
0.25	(0.050)	(0.038)	(0.041)	(0.037)	(0.027)	(0.030)	(0.028)	(0.023)
dip7	0.427***	0.300***	0.364***	0.284***	0.282***	0.072***	0.135***	0.099***
0.5	(0.043)	(0.045)	(0.031)	(0.036)	(0.021)	(0.026)	(0.031)	(0.034)
dip7	0.418***	0.362***	0.348***	0.249***	0.237***	0.066**	0.155***	0.098***
0.75	(0.047)	(0.040)	(0.038)	(0.047)	(0.046)	(0.032)	(0.033)	(0.029)
dip7	0.563***	0.330***	0.251***	0.199***	0.212***	0.095	0.162***	0.107
0.9	(0.133)	(0.072)	(0.070)	(0.062)	(0.080)	(0.064)	(0.049)	(0.076)
dip8	0.735***	0.522***	0.561***	0.711***	0.656***	0.428***	0.497***	0.451***
ols	(0.048)	(0.044)	(0.042)	(0.040)	(0.036)	(0.029)	(0.028)	(0.032)
dip8	0.294**	0.109	0.250	0.590***	0.563***	0.177***	0.258***	0.272***
0.1	(0.150)	(0.098)	(0.177)	(0.088)	(0.094)	(0.064)	(0.084)	(0.052)
dip8	0.604***	0.550***	0.389***	0.640***	0.525***	0.277***	0.415***	0.360***
0.25	(0.083)	(0.083)	(0.068)	(0.064)	(0.049)	(0.034)	(0.043)	(0.068)
dip8	0.744***	0.639***	0.661***	0.702***	0.661***	0.488***	0.541***	0.437***
0.5	(0.038)	(0.042)	(0.045)	(0.045)	(0.033)	(0.027)	(0.038)	(0.041)
dip8	0.788***	0.655***	0.729***	0.637***	0.657***	0.520***	0.585***	0.479***
0.75	(0.074)	(0.039)	(0.052)	(0.040)	(0.044)	(0.033)	(0.039)	(0.063)
dip8	0.989***	0.671***	0.888***	0.796***	0.772***	0.583***	0.709***	0.658***
0.9	(0.155)	(0.096)	(0.101)	(0.108)	(0.057)	(0.108)	(0.093)	(0.109)
dip2*exper	5.890***	4.552***	4.130***	4.628***	3.216***	2.536***	3.393***	3.915***
ols	(0.257)	(0.255)	(0.294)	(0.326)	(0.321)	(0.325)	(0.346)	(0.362)
dip2*exper	5.556***	5.204***	4.703***	6.318***	3.283***	0.797*	3.341***	3.189***
0.1	(0.483)	(0.363)	(0.530)	(0.676)	(0.702)	(0.427)	(0.707)	(0.406)
dip2*exper	5.239***	4.742***	3.483***	3.586***	2.323***	2.154***	2.685***	3.051***
0.25	(0.248)	(0.219)	(0.271)	(0.276)	(0.323)	(0.267)	(0.243)	(0.308)
dip2*exper	4.998***	4.609***	3.755***	3.807***	3.352***	2.790***	3.233***	3.224***
0.5	(0.203)	(0.186)	(0.286)	(0.261)	(0.246)	(0.275)	(0.366)	(0.317)
dip2*exper	5.534***	4.462***	4.022***	3.963***	3.566***	3.289***	3.531***	3.776***
0.75	(0.242)	(0.358)	(0.300)	(0.406)	(0.471)	(0.372)	(0.386)	(0.404)
dip2*exper	5.884***	4.175***	4.030***	4.833***	3.597***	4.321***	5.312***	5.037***
0.9	(0.415)	(0.498)	(0.611)	(0.867)	(0.784)	(0.805)	(0.859)	(0.655)
dip3*exper	9.493***	8.652***	6.878***	5.590***	5.976***	5.262***	6.080***	4.904***
ols	(0.680)	(0.631)	(0.647)	(0.676)	(0.671)	(0.629)	(0.637)	(0.648)
dip3*exper	8.973***	8.053***	4.733***	6.971***	5.272***	4.481***	2.729***	3.560***
0.1	(1.333)	(0.991)	(1.036)	(1.623)	(0.971)	(0.952)	(0.885)	(0.613)
dip3*exper	8.734***	8.728***	5.738***	5.214***	6.084***	5.642***	3.775***	3.185***
0.25	(0.728)	(0.883)	(0.698)	(0.818)	(0.860)	(0.705)	(0.652)	(0.890)
dip3*exper	9.344***	8.350***	6.822***	4.854***	5.450***	5.726***	5.507***	3.761***
0.5	(0.641)	(0.865)	(0.583)	(0.806)	(0.638)	(0.632)	(0.672)	(0.699)
dip3*exper	9.618***	9.875***	6.473***	5.417***	5.312***	5.362***	7.454***	6.083***
0.75	(0.866)	(1.027)	(0.788)	(1.138)	(1.154)	(1.300)	(1.125)	(0.873)
dip3*exper	11.387***	8.701***	8.470***	4.947***	5.784***	5.445***	10.640***	6.648***
0.9	(1.449)	(1.290)	(1.489)	(1.505)	(2.206)	(1.948)	(1.886)	(1.720)
dip4*exper	7.300***	7.147***	4.980***	5.127***	4.764***	4.539***	4.917***	3.914***
ols	(0.311)	(0.289)	(0.297)	(0.293)	(0.286)	(0.276)	(0.267)	(0.278)
dip4*exper	7.605***	7.609***	4.083***	4.744***	3.834***	3.510***	3.562***	2.913***
0.1	(0.597)	(0.426)	(0.396)	(0.449)	(0.411)	(0.243)	(0.489)	(0.435)
dip4*exper	6.544***	6.406***	4.208***	4.177***	3.429***	3.836***	3.734***	3.214***
0.25	(0.249)	(0.302)	(0.245)	(0.216)	(0.237)	(0.257)	(0.298)	(0.292)
dip4*exper	6.548***	6.656***	5.077***	4.293***	3.864***	4.241***	4.339***	3.772***
0.5	(0.276)	(0.278)	(0.237)	(0.240)	(0.223)	(0.245)	(0.236)	(0.332)
dip4*exper	6.745***	7.335***	5.340***	5.231***	4.561***	5.205***	5.751***	3.960***
0.75	(0.374)	(0.326)	(0.340)	(0.488)	(0.386)	(0.332)	(0.281)	(0.337)
dip4*exper	7.741***	6.517***	5.260***	5.190***	4.973***	6.245***	7.603***	4.803***
0.9	(0.524)	(0.542)	(0.576)	(0.581)	(0.596)	(0.591)	(0.513)	(0.638)

to be continued

Table 7: Model (4): QR estimates (3).

	1976	1980	1984	1988	1992	1996	2000	2004
dip5*exper	8.124***	8.219***	7.980***	8.624***	6.820***	9.170***	7.193***	5.744***
ols	(0.793)	(0.724)	(0.744)	(0.767)	(0.727)	(0.576)	(0.532)	(0.503)
dip5*exper	8.330***	6.944***	5.261***	6.088***	4.717***	7.466***	4.763***	4.824***
0.1	(1.266)	(1.210)	(1.026)	(1.471)	(0.972)	(1.265)	(0.841)	(0.649)
dip5*exper	8.494***	9.324***	7.465***	7.771***	4.790***	7.638***	5.598***	4.865***
0.25	(0.912)	(0.896)	(0.978)	(0.729)	(0.596)	(0.760)	(0.476)	(0.534)
dip5*exper	7.972***	8.859***	7.667***	8.815***	6.739***	8.305***	6.032***	5.080***
0.5	(0.906)	(1.021)	(0.798)	(0.733)	(0.797)	(0.617)	(0.513)	(0.545)
dip5*exper	8.219***	8.665***	8.493***	8.771***	8.541***	10.530***	8.262***	5.502***
0.75	(1.161)	(1.129)	(0.962)	(1.135)	(0.822)	(1.109)	(0.503)	(0.868)
dip5*exper	9.903***	8.437***	9.952***	9.984***	8.273***	12.844***	11.327***	6.780***
0.9	(1.760)	(1.552)	(1.676)	(2.131)	(1.987)	(0.948)	(1.194)	(0.971)
dip6*exper	11.716***	10.379***	7.700***	7.261***	6.018***	8.524***	9.237***	9.178***
ols	(0.966)	(0.864)	(0.895)	(0.904)	(0.966)	(0.844)	(0.907)	(0.833)
dip6*exper	9.210***	10.220***	9.315***	7.335***	4.165***	5.789***	6.614***	4.664***
0.1	(1.797)	(2.432)	(2.026)	(2.307)	(1.049)	(2.028)	(1.640)	(1.198)
dip6*exper	9.058***	11.459***	7.336***	4.610***	4.935***	6.847***	7.200***	5.141***
0.25	(1.259)	(1.699)	(1.304)	(1.288)	(1.163)	(1.166)	(0.981)	(1.017)
dip6*exper	9.494***	11.293***	5.990***	6.652***	8.033***	9.321***	9.841***	8.011***
0.5	(1.222)	(1.243)	(1.358)	(1.661)	(1.374)	(1.337)	(1.613)	(1.060)
dip6*exper	13.985***	11.210***	6.317***	6.442***	8.141***	10.300***	11.634***	12.027***
0.75	(1.161)	(1.275)	(1.177)	(1.606)	(1.853)	(1.157)	(1.256)	(1.860)
dip6*exper	16.021***	10.777***	8.271***	9.627***	4.174*	8.065***	8.850***	13.573***
0.9	(2.353)	(2.245)	(2.268)	(2.431)	(2.464)	(2.322)	(2.380)	(2.417)
dip7*exper	10.327***	9.977***	7.929***	9.395***	8.252***	11.567***	9.015***	6.813***
ols	(1.150)	(0.944)	(0.939)	(0.893)	(0.734)	(0.613)	(0.563)	(0.572)
dip7*exper	13.033***	12.006***	8.284***	7.862***	7.704***	10.065***	7.066***	4.340***
0.1	(3.088)	(1.978)	(1.833)	(1.252)	(1.658)	(1.122)	(1.021)	(0.810)
dip7*exper	11.188***	11.034***	8.063***	7.364***	7.344***	10.664***	7.021***	4.852***
0.25	(1.620)	(0.899)	(1.424)	(0.894)	(0.837)	(0.878)	(0.819)	(0.565)
dip7*exper	9.537***	9.908***	6.490***	7.729***	7.761***	10.913***	7.799***	6.622***
0.5	(1.536)	(1.266)	(0.834)	(1.141)	(0.892)	(0.695)	(0.762)	(0.938)
dip7*exper	11.147***	9.344***	8.368***	10.838***	9.737***	12.754***	9.155***	7.914***
0.75	(1.405)	(0.967)	(1.221)	(1.336)	(1.099)	(1.008)	(0.720)	(0.680)
dip7*exper	10.725***	11.200***	10.083***	13.497***	12.185***	13.612***	11.340***	9.142***
0.9	(2.694)	(1.932)	(1.495)	(1.721)	(2.035)	(1.543)	(1.190)	(1.721)
dip8*exper	13.361***	12.082***	11.402***	8.844***	9.279***	11.141***	9.944***	9.301***
ols	(1.063)	(0.955)	(0.870)	(0.909)	(0.839)	(0.623)	(0.597)	(0.661)
dip8*exper	17.556***	16.141***	14.738***	9.317***	7.263***	9.970***	10.157***	7.548***
0.1	(3.910)	(2.811)	(3.801)	(2.877)	(2.634)	(1.703)	(1.647)	(1.635)
dip8*exper	14.745***	10.386***	12.906***	7.726***	10.302***	12.825***	9.296***	8.155***
0.25	(2.349)	(2.040)	(1.946)	(1.504)	(1.487)	(0.801)	(1.051)	(1.548)
dip8*exper	13.317***	11.297***	10.015***	9.286***	9.617***	10.763***	8.696***	9.069***
0.5	(1.166)	(1.098)	(1.002)	(1.368)	(0.994)	(0.784)	(0.990)	(1.123)
dip8*exper	12.602***	11.911***	10.832***	12.129***	10.788***	11.414***	9.838***	10.347***
0.75	(1.728)	(1.001)	(1.409)	(1.242)	(1.253)	(0.964)	(0.918)	(1.594)
dip8*exper	10.921***	11.342***	7.048***	9.800***	8.952***	11.824***	9.946***	8.644***
0.9	(2.935)	(2.010)	(2.049)	(2.402)	(1.579)	(2.442)	(1.866)	(2.263)
dip2*exper2	−17.672***	−12.644***	−10.285***	−12.479***	−5.951***	−3.476**	−7.823***	−13.808***
ols	(1.191)	(1.238)	(1.485)	(1.698)	(1.729)	(1.747)	(1.874)	(1.969)
dip2*exper2	−18.970***	−17.369***	−14.567***	−20.370***	−6.382*	2.816	−10.185***	−11.872***
0.1	(2.089)	(1.505)	(2.399)	(3.093)	(3.414)	(2.348)	(3.344)	(2.059)
dip2*exper2	−17.062***	−14.749***	−8.656***	−8.629***	−3.168*	−3.631**	−6.366***	−10.584***
0.25	(1.251)	(1.123)	(1.412)	(1.417)	(1.907)	(1.515)	(1.353)	(1.807)
dip2*exper2	−14.858***	−13.084***	−8.888***	−9.449***	−7.812***	−5.417***	−8.176***	−10.151***
0.5	(0.971)	(0.888)	(1.396)	(1.372)	(1.471)	(1.604)	(2.108)	(1.855)
dip2*exper2	−15.770***	−11.880***	−8.943***	−9.120***	−7.559***	−5.984***	−8.084***	−12.649***
0.75	(1.147)	(1.908)	(1.743)	(2.308)	(2.678)	(2.074)	(2.410)	(2.527)
dip2*exper2	−14.004***	−8.866***	−8.265**	−13.116***	−6.797*	−9.783**	−15.022***	−17.909***
0.9	(2.116)	(2.387)	(3.298)	(4.659)	(4.027)	(3.946)	(5.358)	(3.896)

to be continued

Table 8: Model (4): QR estimates (4).

	1976	1980	1984	1988	1992	1996	2000	2004
dip3*exper2	-30.121^{***}	-27.547^{***}	-16.395^{***}	-7.868^{*}	-14.967^{***}	-13.801^{***}	-17.617^{***}	-13.477^{***}
ols	(3.702)	(3.552)	(3.796)	(4.085)	(4.101)	(3.739)	(3.789)	(3.809)
dip3*exper2	-34.519^{***}	-30.029^{***}	-13.613^{**}	-22.692^{**}	-16.249^{***}	-15.318^{**}	-2.503	-11.214^{***}
0.1	(7.354)	(6.012)	(6.881)	(9.809)	(5.897)	(6.720)	(6.029)	(3.873)
dip3*exper2	-30.234^{***}	-29.988^{***}	-12.932^{**}	-10.510^{*}	-18.968^{***}	-17.713^{***}	-7.107	-6.622
0.25	(4.698)	(6.215)	(5.041)	(5.498)	(6.335)	(4.906)	(4.430)	(6.094)
dip3*exper2	-30.024^{***}	-25.577^{***}	-14.911^{***}	-4.437	-12.421^{***}	-15.360^{***}	-14.593^{***}	-7.102
0.5	(3.774)	(5.584)	(4.082)	(5.167)	(4.427)	(4.653)	(4.676)	(4.948)
dip3*exper2	-27.582^{***}	-30.919^{***}	-9.675	-4.164	-7.880	-12.971	-23.570^{***}	-17.131^{***}
0.75	(5.590)	(5.291)	(6.251)	(7.431)	(7.494)	(7.940)	(6.831)	(5.801)
dip3*exper2	-32.699^{***}	-21.886^{***}	-19.405^{**}	2.540	-12.217	-11.623	-39.289^{***}	-16.327
0.9	(8.178)	(8.314)	(9.788)	(9.886)	(13.057)	(10.070)	(12.108)	(10.313)
dip4*exper2	-22.876^{***}	-23.234^{***}	-11.336^{***}	-12.041^{***}	-12.056^{***}	-11.703^{***}	-13.668^{***}	-10.098^{***}
ols	(1.747)	(1.683)	(1.774)	(1.736)	(1.673)	(1.613)	(1.555)	(1.622)
dip4*exper2	-28.982^{***}	-29.970^{***}	-13.150^{***}	-14.568^{***}	-11.422^{***}	-10.545^{***}	-10.974^{***}	-9.592^{***}
0.1	(3.290)	(2.784)	(2.632)	(2.487)	(2.263)	(1.652)	(3.018)	(2.408)
dip4*exper2	-22.407^{***}	-21.697^{***}	-9.792^{***}	-10.241^{***}	-7.050^{***}	-10.167^{***}	-10.106^{***}	-9.196^{***}
0.25	(1.726)	(1.948)	(1.769)	(1.433)	(1.582)	(1.462)	(1.610)	(1.724)
dip4*exper2	-20.812^{***}	-21.548^{***}	-11.976^{***}	-8.625^{***}	-8.152^{***}	-10.343^{***}	-11.456^{***}	-10.289^{***}
0.5	(1.803)	(1.678)	(1.610)	(1.601)	(1.422)	(1.579)	(1.430)	(2.032)
dip4*exper2	-18.340^{***}	-22.225^{***}	-10.625^{***}	-11.432^{***}	-9.977^{***}	-14.299^{***}	-16.490^{***}	-7.721^{***}
0.75	(2.363)	(2.332)	(2.497)	(3.357)	(2.687)	(2.045)	(1.863)	(1.951)
dip4*exper2	-20.158^{***}	-15.519^{***}	-8.150^{**}	-8.959^{**}	-10.609^{***}	-17.670^{***}	-25.153^{***}	-9.389^{**}
0.9	(3.274)	(3.361)	(3.760)	(3.573)	(3.831)	(3.608)	(3.569)	(3.843)
dip5*exper2	-25.765^{***}	-23.814^{***}	-26.013^{***}	-27.428^{***}	-16.684^{***}	-30.239^{***}	-19.477^{***}	-12.641^{***}
ols	(4.340)	(4.014)	(4.190)	(4.375)	(4.384)	(3.593)	(3.373)	(3.172)
dip5*exper2	-32.940^{***}	-21.821^{***}	-13.902^{*}	-19.093^{*}	-9.898	-24.580^{***}	-14.066^{**}	-18.695^{***}
0.1	(7.489)	(7.356)	(7.423)	(9.888)	(6.123)	(7.584)	(5.567)	(4.758)
dip5*exper2	-31.376^{***}	-32.824^{***}	-23.667^{***}	-26.610^{***}	-6.832^{*}	-24.446^{***}	-14.365^{***}	-13.273^{***}
0.25	(5.147)	(5.873)	(6.498)	(4.662)	(3.954)	(5.181)	(3.449)	(4.007)
dip5*exper2	-23.903^{***}	-26.457^{***}	-22.960^{***}	-27.643^{***}	-14.098^{**}	-23.829^{***}	-10.446^{***}	-8.353^{**}
0.5	(5.294)	(5.785)	(5.459)	(5.005)	(5.592)	(4.358)	(3.662)	(3.500)
dip5*exper2	-23.189^{***}	-24.546^{***}	-26.101^{***}	-26.190^{***}	-24.686^{***}	-35.057^{***}	-20.610^{***}	-4.861
0.75	(7.136)	(7.320)	(6.142)	(7.493)	(5.355)	(8.209)	(3.494)	(6.293)
dip5*exper2	-34.833^{***}	-23.387^{***}	-35.027^{***}	-33.123^{**}	-23.792^{**}	-48.669^{***}	-38.481^{***}	-8.754
0.9	(10.753)	(8.332)	(9.955)	(13.651)	(11.338)	(5.679)	(8.256)	(5.927)
dip6*exper2	-40.488^{***}	-27.942^{***}	-17.946^{***}	-16.317^{***}	-14.478^{**}	-30.326^{***}	-35.064^{***}	-30.623^{***}
ols	(5.216)	(5.131)	(5.283)	(5.324)	(5.820)	(5.363)	(5.890)	(5.133)
dip6*exper2	-40.087^{***}	-35.985^{*}	-41.667^{***}	-17.046	-2.954	-17.441	-23.530^{*}	-13.288
0.1	(9.729)	(18.967)	(13.434)	(18.054)	(6.987)	(14.733)	(12.277)	(9.068)
dip6*exper2	-30.193^{***}	-38.781^{***}	-20.121^{**}	-0.245	-6.178	-18.815^{**}	-24.590^{***}	-11.374^{*}
0.25	(7.887)	(11.863)	(9.248)	(9.489)	(8.625)	(9.565)	(6.908)	(6.751)
dip6*exper2	-25.569^{***}	-33.214^{***}	-5.645	-12.012	-26.017^{**}	-32.143^{***}	-37.022^{***}	-20.716^{***}
0.5	(7.776)	(8.943)	(8.684)	(10.508)	(10.232)	(9.751)	(10.535)	(7.112)
dip6*exper2	-50.219^{***}	-27.256^{***}	-2.654	-10.739	-30.717^{**}	-39.578^{***}	-45.243^{***}	-43.143^{***}
0.75	(6.890)	(9.225)	(8.629)	(10.195)	(12.425)	(7.418)	(7.663)	(11.606)
dip6*exper2	-53.289^{***}	-22.879	-13.906	-32.061^{**}	-5.519	-25.989^{*}	-27.430^{**}	-49.217^{***}
0.9	(13.654)	(14.252)	(13.709)	(15.480)	(16.050)	(14.692)	(13.367)	(13.602)
dip7*exper2	-33.210^{***}	-31.579^{***}	-16.874^{**}	-27.007^{***}	-23.057^{***}	-43.255^{***}	-25.753^{***}	-11.059^{***}
ols	(7.291)	(6.276)	(6.600)	(6.515)	(5.114)	(4.414)	(3.932)	(3.952)
dip7*exper2	-65.297^{***}	-57.353^{***}	-30.757^{*}	-22.960^{**}	-22.578	-35.292^{***}	-16.572^{**}	-3.990
0.1	(20.246)	(12.445)	(15.916)	(10.110)	(13.761)	(8.870)	(7.085)	(6.144)
dip7*exper2	-47.857^{***}	-44.028^{***}	-27.585^{**}	-18.919^{**}	-20.692^{***}	-40.658^{***}	-14.810^{**}	-2.761
0.25	(13.291)	(6.114)	(12.393)	(7.563)	(6.336)	(7.565)	(6.546)	(4.016)
dip7*exper2	-23.855^{**}	-27.532^{***}	-7.093	-16.079	-21.515^{***}	-39.839^{***}	-18.085^{***}	-10.053
0.5	(11.614)	(9.345)	(7.095)	(9.785)	(8.269)	(5.844)	(6.304)	(6.780)
dip7*exper2	-29.018^{***}	-20.775^{***}	-14.377	-36.501^{***}	-28.828^{***}	-48.753^{***}	-23.749^{***}	-13.175^{***}
0.75	(10.094)	(7.063)	(9.201)	(11.066)	(8.498)	(7.991)	(5.456)	(4.677)
dip7*exper2	-32.372^{**}	-27.958^{**}	-16.115^{*}	-50.015^{***}	-47.259^{***}	-47.291^{***}	-31.290^{***}	-13.888
0.9	(15.395)	(12.946)	(9.555)	(12.908)	(15.386)	(11.617)	(8.976)	(11.219)

to be continued

Table 9: Model (4): QR estimates (5).

	1976	1980	1984	1988	1992	1996	2000	2004
dip8*exper2	−53.022***	−37.249***	−36.559***	−20.944***	−27.478***	−35.756***	−29.363***	−26.775***
ols	(6.232)	(5.711)	(5.086)	(5.900)	(5.539)	(4.216)	(4.148)	(4.634)
dip8*exper2	−83.721***	−60.809***	−60.058***	−25.397	−11.905	−27.572**	−36.778***	−20.170*
0.1	(25.698)	(16.492)	(22.627)	(19.847)	(19.497)	(12.522)	(11.467)	(11.569)
dip8*exper2	−61.740***	−21.891	−39.717***	−13.940	−34.902***	−46.248***	−26.903***	−18.139*
0.25	(16.431)	(13.553)	(13.560)	(11.108)	(11.252)	(5.580)	(7.761)	(10.301)
dip8*exper2	−51.759***	−34.018***	−29.157***	−24.937**	−29.962***	−33.242***	−20.638***	−24.310***
0.5	(7.963)	(7.593)	(6.791)	(10.724)	(7.870)	(5.629)	(7.263)	(8.514)
dip8*exper2	−45.174***	−38.602***	−35.341***	−40.191***	−35.774***	−33.464***	−26.235***	−30.914***
0.75	(10.835)	(6.863)	(9.291)	(9.576)	(8.726)	(7.383)	(6.387)	(11.067)
dip8*exper2	−35.939**	−30.667**	−8.743	−22.726	−19.424*	−34.073**	−17.870	−16.630
0.9	(16.080)	(12.389)	(12.928)	(15.485)	(11.703)	(16.943)	(12.536)	(15.240)
dip2*exper3	15.886***	10.717***	7.535***	10.644***	2.112	0.207	6.457**	19.490***
ols	(1.587)	(1.730)	(2.159)	(2.529)	(2.620)	(2.686)	(2.935)	(3.100)
dip2*exper3	18.591***	16.873***	13.524***	20.714***	1.880	−7.708**	11.426**	16.341***
0.1	(2.719)	(1.912)	(3.291)	(4.201)	(4.926)	(3.759)	(4.916)	(3.018)
dip2*exper3	16.021***	13.658***	5.568***	5.280**	−1.103	1.519	5.651**	14.232***
0.25	(1.738)	(1.594)	(2.117)	(2.112)	(2.994)	(2.489)	(2.219)	(3.051)
dip2*exper3	12.944***	11.144***	5.670***	6.918***	5.459**	3.246	7.859**	13.092***
0.5	(1.298)	(1.240)	(1.974)	(2.079)	(2.398)	(2.572)	(3.495)	(3.078)
dip2*exper3	13.842***	10.189***	5.311*	6.262*	4.503	3.424	7.522*	18.373***
0.75	(1.564)	(2.906)	(2.778)	(3.547)	(4.170)	(3.437)	(4.115)	(4.381)
dip2*exper3	9.741***	5.767*	5.206	12.420*	3.783	7.573	16.607*	26.943***
0.9	(3.016)	(3.358)	(5.142)	(7.150)	(6.155)	(5.771)	(9.418)	(6.514)
dip3*exper3	30.328***	30.415***	12.799**	−0.874	15.354**	17.316***	21.900***	18.993***
ols	(5.569)	(5.550)	(6.217)	(6.784)	(6.943)	(6.317)	(6.472)	(6.438)
dip3*exper3	38.947***	34.669***	12.031	23.351	17.294*	19.825	−4.983	16.041**
0.1	(11.274)	(9.816)	(11.731)	(17.326)	(9.952)	(13.208)	(11.366)	(7.117)
dip3*exper3	31.108***	32.902***	7.244	5.420	22.859*	23.757**	6.456	8.242
0.25	(8.351)	(11.354)	(9.466)	(10.175)	(12.529)	(9.639)	(8.411)	(11.823)
dip3*exper3	31.211***	28.084***	9.231	−4.852	12.219	19.909**	18.603**	8.763
0.5	(6.090)	(9.544)	(7.873)	(8.829)	(8.184)	(9.116)	(8.788)	(9.671)
dip3*exper3	27.707***	35.385***	1.725	−5.803	3.808	17.752	33.637***	25.079**
0.75	(9.630)	(7.584)	(12.534)	(13.294)	(13.464)	(13.665)	(11.833)	(10.398)
dip3*exper3	31.225**	19.473	17.251	−19.901	13.868	13.686	55.718***	20.915
0.9	(12.522)	(14.480)	(16.551)	(16.950)	(21.434)	(14.851)	(21.381)	(17.532)
dip4*exper3	22.208***	24.636***	6.557**	8.513***	10.189***	11.191***	13.960***	11.498***
ols	(2.728)	(2.739)	(2.959)	(2.871)	(2.745)	(2.696)	(2.599)	(2.714)
dip4*exper3	32.972***	35.396***	13.374***	13.769***	10.221***	10.546***	11.623**	12.406***
0.1	(5.059)	(4.873)	(4.678)	(4.008)	(3.632)	(3.048)	(5.338)	(3.894)
dip4*exper3	22.964***	22.703***	5.249	6.999***	2.973	9.345***	9.753***	10.643***
0.25	(3.159)	(3.370)	(3.246)	(2.485)	(2.870)	(2.483)	(2.551)	(2.808)
dip4*exper3	20.958***	22.692***	7.176**	4.056	4.814*	9.208***	11.427***	12.383***
0.5	(3.101)	(2.810)	(3.086)	(2.797)	(2.491)	(2.815)	(2.543)	(3.536)
dip4*exper3	15.610***	22.984***	4.448	8.029	8.222	16.026***	18.372***	6.755**
0.75	(3.902)	(4.307)	(4.804)	(6.067)	(5.094)	(3.601)	(3.376)	(3.257)
dip4*exper3	16.234***	13.512**	1.617	4.203	8.976	21.490***	33.254***	8.712
0.9	(5.683)	(5.720)	(6.624)	(6.083)	(6.530)	(6.191)	(6.962)	(6.513)
dip5*exper3	26.057***	21.414***	30.069***	29.596***	11.566	35.180***	20.669***	12.247**
ols	(6.704)	(6.269)	(6.692)	(7.104)	(7.374)	(6.168)	(5.941)	(5.631)
dip5*exper3	38.314***	17.691	10.200	18.939	2.042	25.673**	15.959	29.444***
0.1	(11.912)	(12.443)	(14.064)	(17.892)	(10.388)	(13.064)	(10.381)	(8.951)
dip5*exper3	34.627***	35.378***	24.115**	30.416***	−5.510	26.214***	14.057**	17.756**
0.25	(7.789)	(10.484)	(11.989)	(8.931)	(7.182)	(9.433)	(6.687)	(7.810)
dip5*exper3	21.895**	24.457***	24.926**	28.935***	4.894	23.825***	3.816	5.040
0.5	(8.689)	(9.034)	(9.988)	(8.975)	(10.387)	(8.245)	(7.201)	(6.345)
dip5*exper3	20.894*	23.875*	30.021***	27.881*	24.929**	43.343***	19.529***	−4.058
0.75	(12.001)	(12.931)	(10.357)	(14.268)	(9.828)	(15.791)	(6.793)	(11.672)
dip5*exper3	45.614**	24.707*	45.256***	41.244*	26.192	66.378***	51.837***	1.106
0.9	(18.757)	(12.939)	(17.082)	(23.917)	(18.162)	(9.361)	(15.296)	(11.131)

to be continued

Table 10: Model (4): QR estimates (6).

	1976	1980	1984	1988	1992	1996	2000	2004
dip6*exper3	42.641***	20.358**	11.595	9.342	16.530*	43.409***	52.058***	39.657***
ols	(7.862)	(8.500)	(8.710)	(8.760)	(9.790)	(9.617)	(10.931)	(9.099)
dip6*exper3	47.243***	33.807	56.135**	1.880	−11.998	20.882	30.271	18.311
0.1	(14.469)	(36.930)	(24.226)	(34.589)	(13.234)	(28.117)	(25.351)	(18.742)
dip6*exper3	29.523**	38.612*	15.228	−18.823	−1.356	21.914	36.771**	13.890
0.25	(12.831)	(21.090)	(16.673)	(19.006)	(17.550)	(20.194)	(14.289)	(12.621)
dip6*exper3	18.433	29.969*	−10.214	2.711	35.045*	43.242**	55.461***	19.409
0.5	(13.421)	(17.081)	(15.384)	(18.906)	(20.616)	(18.818)	(18.906)	(14.002)
dip6*exper3	58.902***	18.916	−15.792	5.650	51.166**	60.586***	66.465***	56.876***
0.75	(11.365)	(17.557)	(16.510)	(18.692)	(23.000)	(13.901)	(14.647)	(20.296)
dip6*exper3	57.930***	11.216	4.142	43.889*	12.097	39.913	32.197	65.663***
0.9	(20.644)	(24.142)	(22.788)	(26.437)	(28.586)	(25.204)	(21.830)	(21.882)
dip7*exper3	33.541***	31.217***	3.603	23.715*	21.179**	58.993***	26.998***	0.831
ols	(12.354)	(11.372)	(12.545)	(12.926)	(9.797)	(8.929)	(7.780)	(7.805)
dip7*exper3	89.702***	82.754***	29.031	14.163	13.395	36.737*	4.887	−6.369
0.1	(33.691)	(22.841)	(34.548)	(20.815)	(29.693)	(18.877)	(13.536)	(12.831)
dip7*exper3	63.553**	54.580***	28.693	8.699	17.222	57.023***	5.128	−11.584
0.25	(26.299)	(10.463)	(28.092)	(17.950)	(13.955)	(17.912)	(14.215)	(8.026)
dip7*exper3	14.653	21.471	−12.471	5.849	23.754	55.038***	14.106	−1.430
0.5	(20.184)	(17.622)	(14.686)	(21.982)	(19.129)	(14.008)	(14.132)	(13.932)
dip7*exper3	21.205	7.939	−1.040	48.957*	33.341*	70.282***	24.494**	1.481
0.75	(17.860)	(13.438)	(16.798)	(25.342)	(17.905)	(17.223)	(11.450)	(8.818)
dip7*exper3	33.752	16.916	−7.084	66.697**	70.772**	62.780***	35.396*	−3.118
0.9	(24.955)	(22.651)	(16.709)	(25.896)	(31.580)	(23.883)	(18.331)	(21.820)
dip8*exper3	65.585***	30.967***	33.249***	9.214	27.993***	40.835***	33.290***	32.602***
ols	(10.291)	(9.746)	(8.484)	(10.659)	(10.120)	(7.944)	(8.086)	(9.192)
dip8*exper3	108.714**	60.411**	63.502*	6.675	−11.406	20.768	51.085**	22.478
0.1	(48.880)	(26.983)	(36.221)	(36.601)	(39.020)	(26.472)	(22.958)	(22.204)
dip8*exper3	78.285**	−6.390	25.122	−3.844	40.054*	57.134***	27.733*	11.410
0.25	(31.149)	(25.587)	(25.840)	(22.576)	(23.209)	(10.653)	(16.228)	(19.793)
dip8*exper3	63.032***	30.932**	24.912*	18.840	32.834**	35.639***	15.737	25.765
0.5	(14.269)	(14.585)	(14.036)	(22.288)	(16.610)	(11.145)	(14.492)	(18.352)
dip8*exper3	54.998***	40.679***	38.854**	44.163**	46.095***	34.556**	29.238**	39.903*
0.75	(18.600)	(13.147)	(17.307)	(18.581)	(16.090)	(14.677)	(12.840)	(20.953)
dip8*exper3	41.896*	23.548	−4.886	16.769	12.610	38.622	6.540	18.021
0.9	(24.777)	(22.108)	(23.577)	(27.529)	(22.508)	(31.695)	(22.343)	(32.130)
Joint F-test	20.1***	18.4***	17.6***	16.8***	14.2***	27.7***	25.6***	19.1***

***: p-value$<$ .01, **: p-value$<$ .05, *: p-value$<$ .1. Bootstrapped standard errors obtained with 50 replicates are reported in parentheses.

Table 11: Model (4): tests for location-shift and location-scale-shift models (1).

	1976	1980	1984	1988	1992	1996	2000	2004
				Tests for a location-shift model H_{01}				
F-stat for Wald test of joint $H_0 1$ (1)	20.1***	18.4***	17.6***	16.8***	14.2***	27.7***	25.6***	19.1***
F-stat for Wald test of univariate subhypotheses (1)								
dip3	0.8	1.0	5.4***	1.7	4.7***	3.2**	1.8	0.9
dip4	0.7	3.0**	5.9***	5.4***	3.0**	0.7	1.8	1.2
dip5	0.8	1.2	1.8	4.2***	0.9	1.3	2.4**	0.6
dip6	0.4	0.3	1.6	1.5	9.4***	24.8***	4.7***	0.9
dip7	1.1	2.2*	1.4	2.2*	1.4	3.1**	0.3	1.3
dip8	2.4**	3.3**	10.6***	1.7	4.8***	15.6***	6.1***	8.0***
dip2*exper	2.2*	0.9	3.2**	6.4***	6.1***	6.0***	3.6***	2.5**
dip3*exper	1.3	1.3	2.2*	0.7	0.3	0.9	8.3***	4.2***
dip4*exper	3.3**	6.5***	3.6***	3.5***	3.1**	5.9***	13.6***	2.4**
dip5*exper	0.7	2.6**	2.3*	2.0*	4.7***	8.7***	10.0***	0.9
dip6*exper	4.4***	0.1	0.9	2.0*	4.1***	2.0*	2.1*	3.6***
dip7*exper	0.7	0.9	2.8**	5.0***	2.4**	2.6**	2.6**	6.9***
dip8*exper	0.4	0.7	2.2*	1.8	1.7	3.2**	0.6	0.8
dip2*exper2	1.8	2.4**	2.7**	6.0***	3.5***	3.0**	1.6	1.3
dip3*exper2	0.3	0.7	0.5	1.4	0.7	0.1	4.7***	1.6
dip4*exper2	3.8***	7.4***	1.3	2.4**	2.0*	1.5	4.3***	0.7
dip5*exper2	1.3	1.6	1.5	0.7	2.8**	6.4***	3.6***	1.7
dip6*exper2	3.6***	0.3	2.2*	1.6	4.2***	1.1	1.1	1.7
dip7*exper2	1.7	3.3**	1.6	3.5***	1.1	0.8	0.6	1.2
dip8*exper2	0.7	1.0	2.0*	1.2	1.7	2.9**	1.1	0.5
dip2*exper3	2.3*	2.0*	2.5**	6.1***	2.7**	2.2*	1.1	1.7
dip3*exper3	0.1	0.7	0.4	1.2	0.7	0.1	4.9***	1.2
dip4*exper3	4.8***	6.8***	1.6	2.5**	2.1*	1.4	2.9**	1.1
dip5*exper3	2.1*	1.7	1.6	0.5	2.9**	6.8***	2.9**	2.9**
dip6*exper3	3.7***	0.3	2.4**	1.5	5.0***	0.8	0.9	1.1
dip7*exper3	1.8	5.2***	1.1	3.7***	1.1	1.3	0.6	0.5
dip8*exper3	0.5	1.2	1.4	1.0	2.0*	2.7**	1.9	0.4
Khmaladze stat for joint H_{01} (2)	97.0***	82.8***	102.7***	111.8***	85.4***	63.9***	126.5***	149.5***
Khmaladze stat for univariate subhypotheses (2)								
dip3	1.2	1.1	1.8	0.4	1.5	2.1**	0.4	0.6
dip4	0.6	1.6	1.1	1.2	0.7	1.0	1.4	0.3
dip5	0.6	1.3	1.3	0.9	0.6	0.7	0.3	0.8
dip6	0.7	0.8	1.0	1.9*	1.1	1.1	1.6	0.6
dip7	0.4	1.1	0.5	2.1**	0.7	0.7	0.9	1.5
dip8	1.4	1.5	2.0*	1.1	1.3	2.5**	1.0	0.9
dip2*exper	1.1	0.4	1.2	1.2	2.7***	0.8	0.8	1.1
dip3*exper	0.6	1.8	0.9	2.1**	0.4	0.9	1.0	0.8
dip4*exper	0.4	2.2**	1.0	2.6**	2.4**	2.2**	2.9***	1.6
dip5*exper	0.3	1.3	0.6	1.4	2.3**	2.0*	2.1*	0.4
dip6*exper	2.5**	1.1	0.5	1.1	1.4	2.2**	1.3	1.6
dip7*exper	0.8	1.1	0.8	0.9	1.8	1.5	1.9*	0.8
dip8*exper	0.8	0.9	1.5	1.4	1.1	1.2	0.4	0.5
dip2*exper2	0.5	0.5	0.7	0.6	1.8*	0.3	0.5	0.8
dip3*exper2	1.1	1.3	0.7	1.4	1.5	0.7	0.4	0.7
dip4*exper2	0.9	1.8	0.7	1.4	1.2	2.0*	1.6	0.8
dip5*exper2	0.5	1.2	0.8	0.9	1.9*	1.5	0.5	1.4
dip6*exper2	2.4**	0.5	0.3	1.1	1.4	2.3**	1.2	1.2
dip7*exper2	0.7	1.3	0.5	1.0	1.2	0.5	1.3	0.5
dip8*exper2	0.7	1.2	2.3**	1.2	1.2	1.2	0.4	0.6
dip2*exper3	0.6	0.7	0.6	0.5	1.7	0.4	0.7	0.8
dip3*exper3	0.8	1.2	0.5	1.2	1.9*	0.7	0.6	0.7
dip4*exper3	0.8	1.8	0.5	1.2	1.3	2.1*	1.1	0.8
dip5*exper3	0.5	1.0	0.7	0.8	1.9*	1.3	0.5	1.7
dip6*exper3	2.5**	0.3	0.4	1.1	1.4	2.4**	1.0	1.2
dip7*exper3	1.3	1.1	0.5	0.5	1.1	0.4	1.2	0.5
dip8*exper3	0.5	1.3	2.4**	1.0	1.4	1.1	0.5	0.7

to be continued

Table 12: Model (4): tests for location-shift and location-scale-shift models (2).

	1976	1980	1984	1988	1992	1996	2000	2004
			Tests for a location-scale-shift model H_{02}					
Khmaladze stat for joint H_{02} (2)	28.6^{***}	37.4^{***}	32.5^{***}	29.6^{***}	24.5	20.2	26.3^{**}	17.8
Khmaladze stat for univariate subhypotheses (2)								
dip3	1.0	0.6	1.1	0.6	0.5	0.7	0.3	0.8
dip4	0.7	0.4	1.3	0.8	0.7	1.0	0.2	0.3
dip5	0.6	1.0	1.2	0.8	0.7	1.0	0.7	0.6
dip6	0.8	0.4	0.4	0.9	1.3	1.0	1.9*	0.4
dip7	0.5	0.9	1.1	0.8	1.2	0.5	0.6	1.1
dip8	1.7	1.4	1.2	1.0	1.2	1.6	0.6	0.9
dip2*exper	0.3	0.4	1.2	0.5	0.5	0.8	0.3	0.4
dip3*exper	1.2	0.8	1.0	0.8	0.3	0.8	0.6	0.4
dip4*exper	0.6	0.6	0.9	0.7	0.5	0.5	0.3	0.3
dip5*exper	0.2	1.0	0.7	0.5	0.9	0.9	0.8	0.3
dip6*exper	0.8	0.4	0.2	1.2	1.8	1.4	1.8	0.4
dip7*exper	0.7	1.3	0.6	1.0	1.1	0.5	0.9	0.8
dip8*exper	1.1	1.2	0.9	0.7	1.3	1.0	0.9	1.1
dip2*exper2	0.4	0.5	1.0	0.6	0.5	0.7	0.7	0.3
dip3*exper2	1.1	0.7	1.1	0.5	0.4	0.7	0.7	0.7
dip4*exper2	0.7	0.6	0.8	0.7	0.5	0.5	0.4	0.4
dip5*exper2	0.4	1.4	0.9	0.6	0.5	1.3	1.0	0.3
dip6*exper2	0.9	0.4	0.3	0.9	1.9*	1.3	1.2	0.5
dip7*exper2	0.8	1.3	0.6	0.7	1.0	0.5	1.0	0.8
dip8*exper2	0.8	1.0	0.8	0.6	1.2	0.7	1.1	1.1
dip2*exper3	0.4	0.4	0.9	0.6	0.4	0.8	0.9	0.3
dip3*exper3	1.0	0.6	1.0	0.5	0.6	0.5	0.6	1.1
dip4*exper3	0.7	0.5	0.8	0.7	0.5	0.4	0.5	0.5
dip5*exper3	0.5	1.5	1.0	0.7	0.4	1.5	0.8	0.3
dip6*exper3	0.9	0.3	0.3	0.7	1.9*	1.2	0.9	0.5
dip7*exper3	0.8	1.4	0.5	0.6	0.9	0.4	1.0	0.8
dip8*exper3	0.6	0.9	0.6	0.5	1.0	0.6	1.1	1.1

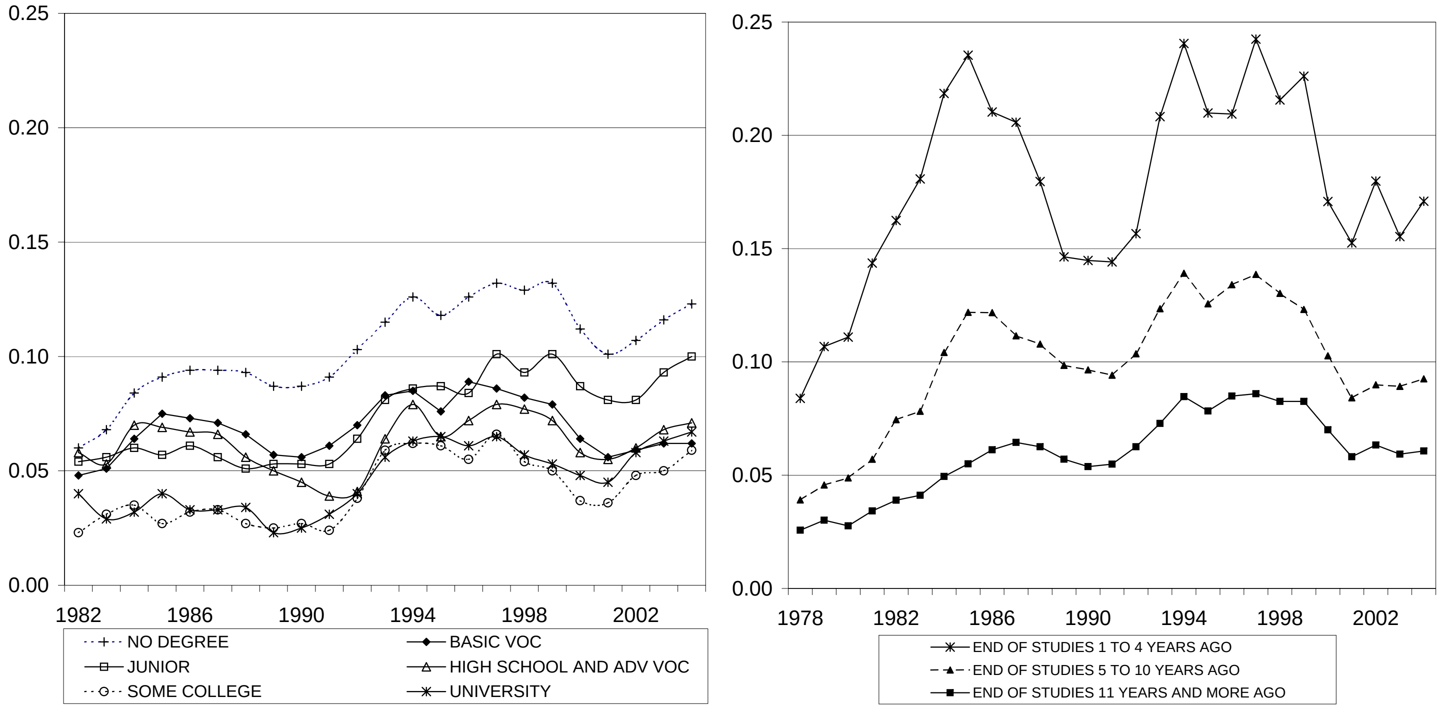
***: p-value$<$ .01, **: p-value$<$ .05, *: p-value$<$ .1.

(1) Wald tests for equal quantiles parameters at order .1, .25, .5, .75 and .9, see Koenker and Bassett (1982). F-stat are reported.

(2) To construct Koenker and Xiao (2002) tests for H_{01} and H_{02}, quantile regressions were performed at orders .1 to .9 by .05 increase. The critical values used are those reported in Table B.1. and B.2. p 318 in Koenker (2005) or were computed thanks to Koenker and Xiao (2002) programs, which were kindly provided by Zhijie Xiao.

Quantile regressions and tests were performed in R with the quantile regression package `quantreg`, see Koenker (2005).

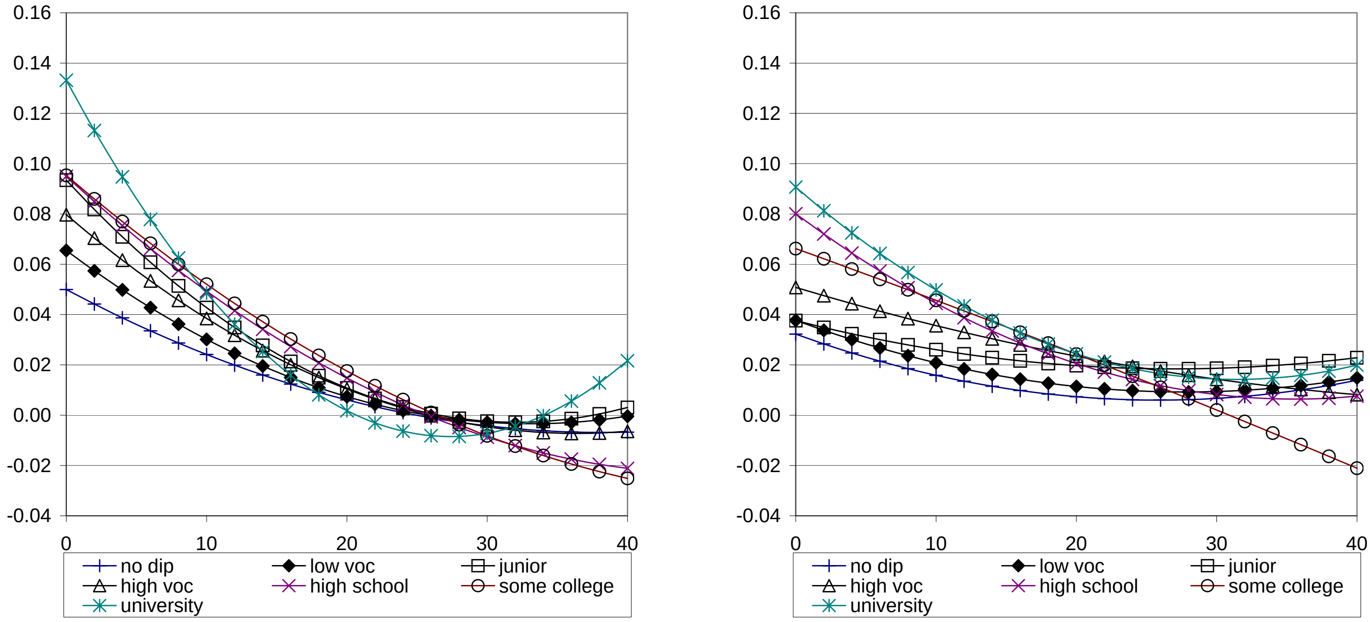
D Additional graphics



(a) male unemployment rate by education groups (INSEE)

(b) male unemployment rate by potential experience (INSEE)

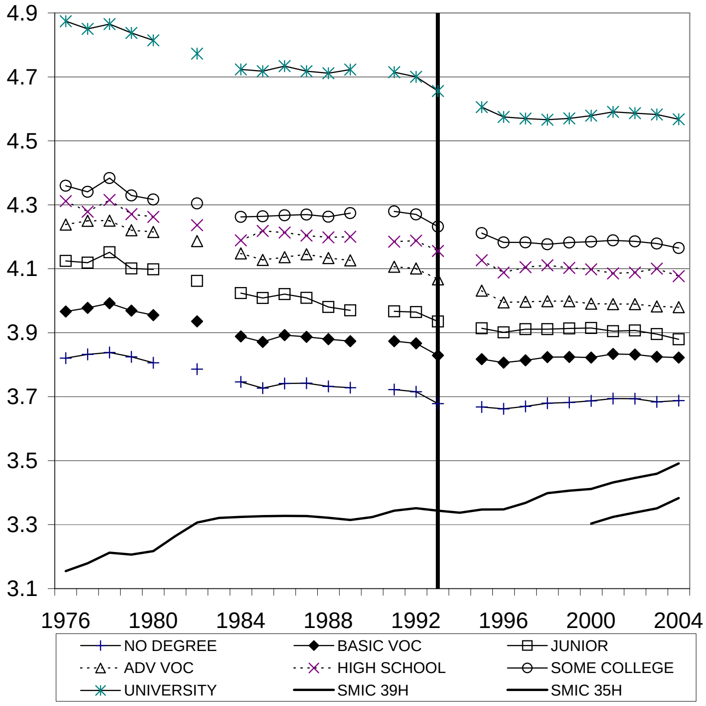
Figure 13: Male unemployment rates by education groups and potential experience



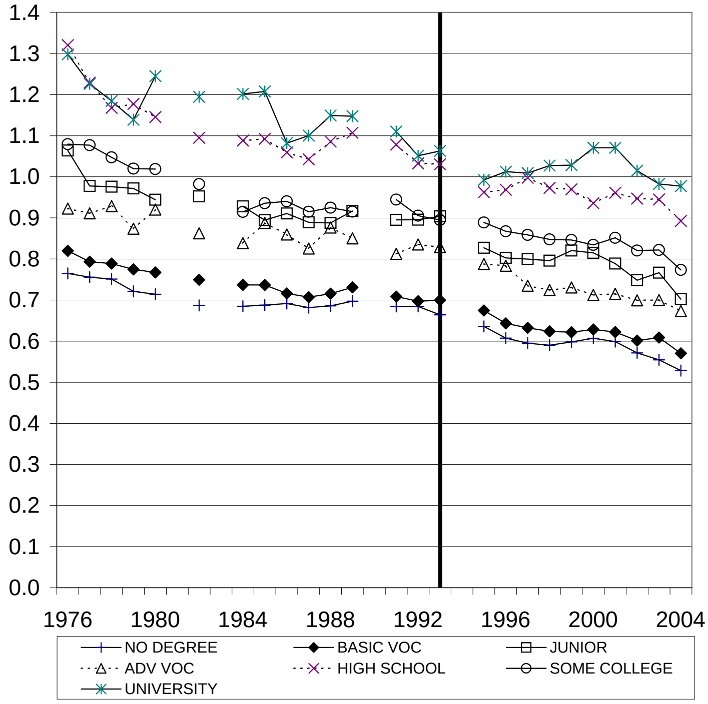
(a) 1976

(b) 2004

Figure 14: Model (4): LAD estimates of marginal effects of experience.



(a) LAD adjusted log wages



(b) Q90-Q10 log wages differences

Figure 15: Specification with age: adjusted log wages and Q90-Q10 log wage differences at 30 years old