Decreasing Wage Inequality in France 1976-2004: Another French Exception?[☆]

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Abstract

The increase in overall wage inequalities seems to be a structural trend in Western countries such as the United Kingdom (U.K.), the United States (U.S.), Canada and Germany, but not in France. This paper studies changes in wage differentials across 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 control for composition effects. We disentangle between- and within-education group wage inequalities and we describe their evolutions separately. We use annual employer-employee administrative data matched with census data.

Our main results are as follows. (1) The overall wage inequality was stable from 1976 to 1992 and decreased slightly from 1995 to 2004 due to a decrease in lower-tail inequality. (2) Between-education group wage inequalities decreased over the entire period due to decreasing education premiums, particularly at low levels of experience. (3) Within-education group wage inequalities were fairly stable from 1976 to 1992 and decreased between 1995 and 2004, especially at low levels of experience. (4) Composition effects due to increasing educational attainment over the period may have obscured the significant decreases in both between- and within-education group wage inequalities.

The main force that seems to drive these changes is the minimum wage rise over the period. Supply and demand effects and unemployment pressure on wages may have contributed to these changes, but the evidence is less clear.

Keywords: wage inequality, within-education group inequality, between-education group inequality, education return heterogeneity, quantile regressions, minimum wage.
JEL codes: C21, J31, I24.

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1. Introduction

Changes in wage inequality can be driven by several factors which are usually classified into two groups: market and non-market factors. Market factors include education supply and demand, while non-market factors include labour-force composition effects and minimum wage changes. These factors can interact in the same or opposite directions and it is often difficult to determine a "unicausal" explanation. However, empirical analysis can provide some evidence on the most relevant factors.

Changes in wage inequality have been scrutinised in the literature since the 1990s and mainly in the U.S. (see, for example, Juhn et al., 1993). An important issue is to explain the enormous increase in wage inequalities in the U.S. since the 1980s by proposing decomposition methods to disentangle labour force composition effects and "price effects". An open and strongly debated question concerns the main factors that drive changes: are the increasing wage inequalities evidence of skill-biased technological change (as in Katz and Murphy, 1992; Acemoglu, 2002; Autor et al., 2008) or are these changes driven by non-market factors, particularly minimum wage changes and the spurious consequences of educational composition effects (as in DiNardo et al., 1996; Lee, 1999; Card and DiNardo, 2002; Lemieux, 2006a)? To validate the skill-biased technological change hypothesis, similar evolutions of education premiums and residual inequalities (once controlled by education) are expected to be found in most Western countries as such market factors should affect these countries in a similar way. Over the 1980s and the 1990s, education premiums actually increased in most studied countries, i.e. the U.S., Portugal (Machado and Mata, 2005), Canada, the U.K. (Card and Lemieux, 2001), Germany (Dustmann et al., 2009), but not always at the same period and more or less strongly. In most of the studied countries, residual inequalities also increased (the U.S., the U.K., Canada, Portugal, Germany and Italy). This could give some support to the skill-biased technological change hypothesis but they are some notable exceptions where education premiums fell : Austria (Fersterer and Winter-Ebmer, 2003) and Italy (Naticchioni and Ricci, 2009) or residual inequalities decreased (Austria). In France, even the overall wage inequality evolution is very different from that of the U.S., the U.K. or Germany. While for the latter, the overall wage inequality increased between the mid-70s and the mid-2000s, it was stable or slightly decreased in France, see figure 1.[3] An investigation of other possible factors of inequality changes is thus necessary.

In this paper, we use annual employer-employee administrative data matched with the Census to draw a complete picture of the French wage inequality patterns over approximately thirty years, 1976-2004. Over this period, the French labour market faced significant changes. However, overall wage inequality, measured as the Q90-Q10 wage gap, remained stable from the mid-1970s to the mid-1990s and then decreased slightly. This decrease was driven mainly by a decrease in lower-tail inequality, measured as the Q50-Q10 wage gap. Contrary to the U.S., the U.K. or Germany, upper-tail wage inequality, measured as the Q90-Q50 wage gap, did not increase over the period considered.[4] It is crucial to precisely document the evolution of wage distribution because it is affected differently by competing explanations. We therefore run quantile regressions on Mincer-type equations and we control for skill – experience and education – composition effects. We disentangle between- and within- education group wage inequalities (in other words, educations premiums and residual inequalities) and describe their evolutions.

Beyond the relative stability or slight decrease in overall wage inequalities, we document a strong decrease in between- and within-education group wage inequalities in France over 1976-2004. The strong

[3] We use OECD data for full time male workers on net wages for France and gross wages for the other countries.

[4] Two papers document a strong increase in top wages growth since the end of the 1990s in France but, at this stage, those 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).

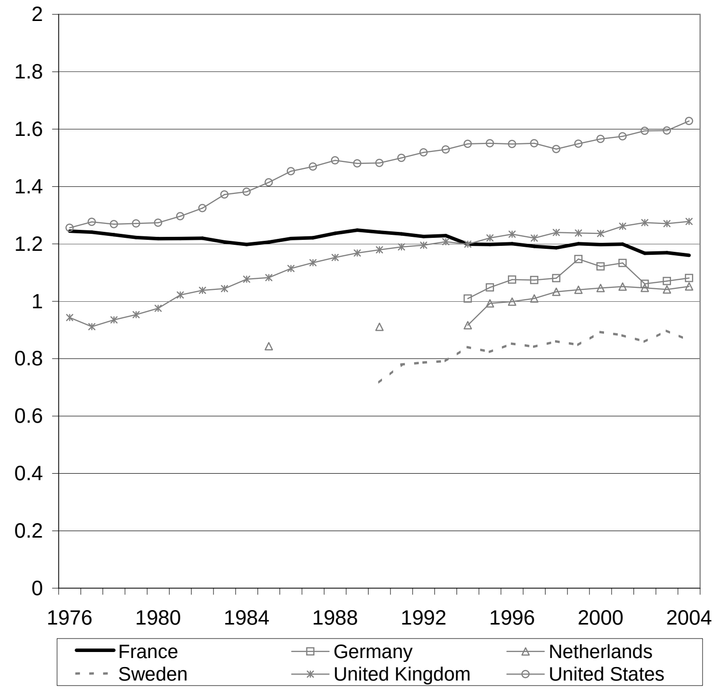


Figure 1: International comparisons of Q90-Q10 log wage inequalities for male

increase in educational attainment of the labour force over the period may have counterbalanced these decreasing structural trends and contributed to maintaining a relatively high and stable level of overall wage inequality. The decrease in education premiums (between-inequalities) was stronger between the mid-1970s and the mid-1980s and after the mid-1990s. Within education groups, wage inequalities have mainly decreased since the mid-1990s. The previous studies on French data mainly focus on mean effects, see Goux and Maurin (1994), Bayet and Cases (1996) and Selz and Thélot (2003) and also find decreasing education premiums. Crépon and Gianella (1999) run quantile regressions on four waves of survey data (*Formation et Qualification Professionnelle*) between 1976 and 1993.[5] They find similar results about within-inequalities on that period. Once we allow for heterogeneous effects of experience by education groups, we find that these changes are driven by trends of less experienced workers.

A compelling explanation for the decrease in between- and within-education group wage inequalities is the huge increase in the minimum wage over the period. This explanation is consistent with a decrease in lower-tail inequality. It is also consistent with a larger decrease in between- and within- inequalities for the lower-paid workers (i.e. the less educated and the less experienced workers). This primary effect may have interacted with the increasing supply of highly educated workers over the period and the pressure on wages induced by increasing unemployment. However, the evidence for the latter two explanations is less clear. Our empirical results do not provide further evidence of the skill-biased technological change hypothesis.

[5] Recently, Verdugo (2011) applies the decomposition method proposed by DiNardo et al. (1996) to study the effect of the supply and demand education factor on the French wage structure.

This paper focuses on wage differentials across education groups for full-time male workers[6] in the French private sector from 1976 to 2004. The data we use come from a new match between the DADS panel (déclaration annuelle de données sociales) and the Census EDP database (échantillon démographique permanent) over the period 1976-2004. The DADS panel is a special subsample of the DADS, an exhaustive administrative database of annual employer-employee wage bill information which is compulsory for all firms. It contains information on a sample of wage earners (1/12), including wages paid, working periods and private sector employers. The education information is extracted from the Census EDP database. With this new matched dataset, we can exploit wage information on working periods in the private sector for each year between 1976 and 2004.[7] However, the dataset does not contain information on unemployed individuals or those working in the public sector.

Quantile regression estimates of various orders are used to compute the measures of within-education group wage inequality adjusted for experience. For each education group, we compute the Q90-Q10, Q90-Q50, and 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 the median wage comparisons.

Quantile regressions are useful tools for analysing changes in the wage distribution and in the heterogeneity of the skill premiums. Whereas the OLS method only provides information on average returns, quantile regressions facilitate examination of the entire conditional wage distribution. Following the seminal paper of Koenker and Bassett (1978), Buchinsky (1994) was the first to investigate the sources of wage inequality evolutions in the U.S. using quantile regressions. Since then, the methods have been applied in numerous countries, but rarely in France.[8] The only papers we are aware of are Crépon and Gianella (1999) and Martins and Pereira (2004), the latter of which also analyses other European countries.[9]

The baseline model considered in this paper is a classic Mincer equation, with education and experience – degree dummies and third-order effects of experience. We also consider an alternative specification in which education and experience are interacted. This specification accounts for the non-separability of the two human capital types (see Rubinstein and Weiss, 2006; Belzil, 2006; Heckman et al., 2006). Workers who are more educated usually receive training opportunities and promotions more easily and they may be able to acquire or use skills faster than others. This may be related to unobserved education group abilities or to an indirect effect of education. Experience is apparently rewarded differently based on education group, which accounts for the observed non-parallelism of the log-earnings experience profiles (see, for example, Murphy and Welch, 1990; Murphy and Welch, 1992; Autor and Katz, 1999). When we allow for different education-group-rewarding profiles of experience, it appears that education had a directly positive impact on hiring wages in the 1970s and the 1980s, but this effect disappeared at the beginning of the 1990s – except for university degree holders. Since then, the channel through which the education affects the wages has been closely related to the experience-rewarding profile and the experience accumulation process. In terms of evolution, the decreases in between- and within-education group wage inequalities over the period are mainly driven by decreases for the less experienced workers.

[6]The analysis is restricted to male wage earners to limit labour market participation issues. Papers in the literature run separated regressions for men and women (see Lemieux, 2006b or Autor et al., 2008) or only focus on men (Dustmann et al., 2009).

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

[8]See amongst others: Fortin and Lemieux (1998), Gosling et al. (2000), Martins and Pereira (2004), Machado and Mata (2005), Autor et al. (2005)

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

The paper is organised as follows. Section 2 presents the data used. Section 3 describes the raw trends in wage inequalities, education and experience levels. Section 4 is dedicated to the Mincer quantile regression model. Section 5 contains the presentation of the resulting between- and within-education group wage inequality changes and the potential explanations for these evolutions are compared empirically. Section 6 describes between- and within-education group wage inequality evolutions entailed by the alternative model, in which education and experience are interacted. Section 7 contains some sensitivity analyses. Section 8 concludes.

2. Data

The data come from the match between the individual panel subsample of the DADS and the census EDP dataset. The wage and experience variables are constructed using information from the DADS dataset and the education variables from the EDP dataset.[10]

The DADS is an exhaustive administrative database of annual employer-employee wage bill information with compulsory completion by any firm establishment. It contains information on wages, working periods and private sector employers of wage earners born at chosen dates. The EDP database collects census information (e.g. education, family status at the census dates) and civil state administrative information (e.g. date of marriage, child birth). The coherence between birth dates of individuals in both files and the exhaustive nature of both files make it possible to match information for individuals born in France. For people born abroad, matching is not possible. The restriction to individuals born in France reinforces the likelihood that these individuals attended school in France and were affected by French legislation concerning the minimum age for leaving school. Some corrections applied to the data rely on this legislation.

2.1. Variables

The variables used in the analysis are wage, highest degree obtained (education) and experience accumulated as a wage earner in the private sector. The wage variable is the net real daily wage in 2004 euros, that is, the sum of net earnings in real terms divided by the number of working days for a given working period. We constructed the education and the experience variables. We present in detail in the appendix the different steps of construction and our corrections.

The education level is indicated by the highest degree obtained at the end of studies, which is coded in 7 categories: no degree reported or elementary school level, junior high school degree, basic vocational degree, advanced vocational or technical degree, high school degree (BAC), some college (BAC+1, BAC+2) and university degree (BAC+3 and more). Their precise descriptions and their French labels are reported in Table A.5 in the appendix together with their shares of the panel population. These categories are very similar to the ones used by Abowd et al. (1999).

The experience variable refers to the experience accumulated as a wage earner in the private sector. It sums the share of working days per year from a given individual's first appearance in the DADS panel to the current working period. Note that there is no distinction between experience accumulated when working during studies and experience accumulated after completing studies. The experience variable 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 studies is valuable.

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

Other constructed variables included the age upon leaving school and the year leaving school, which are used to restrict the sample and the experience accumulation to non-student periods of work. For more details, see the appendix.

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- to 64-year-old male private sector wage earners born in France. To ensure that the wage distribution is representative of the total number of days worked in the economy, we weight the working periods by the number of working days for which they account in the regressions. 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 as in a Mincer-type equation. We also exclude student working periods because the level of education attained at this point is unknown. We only have information on educational attainment at the end of 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. Therefore, we use information from the 1968, 1975, 1982, 1990 and 1999 censuses and three annual census surveys conducted in 2004, 2005 and 2006. The latter cover roughly one-third of the population. Consequently, education is collected for only one-third 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 collected directly, but since 1994, it has been corrected automatically and reported full-time workers with hourly wages less than 80% of the legal minimum hourly wage are put in the part-time category. This change may entail breaks in wage evolution, especially at the bottom of the distribution for some education groups, even if the breaks do not clearly appear in descriptive statistics. Consequently, we do not interpret evolution over the entire period but only for the two sub-periods 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 full-time if he works more than 80% of the legal or conventional working time (see Demailly and Le Minez, 1999). Finally, outliers are cancelled out. We eliminate the observations such that $|\ln(\text{wage}) - q50| > 5 \times |q75 - q25|$, as in Crépon and Gianella (1999). The sample used in the analysis contains approximately 100,000 individuals and 45,000 observations per year.

3. The slow evolution of wage inequalities over 1976-2004 hides dramatic labour market structure changes

Figure 2a displays the evolution of the following inequality measures for full-time male workers:[11] Q90-Q10, Q50-Q10, Q90-Q50 log wage differences, and the Gini coefficient of the log wage distribution. The overall wage inequalities in France were rather stable-a slow decrease during the late 1970s compensated by a slow increase during the late 1980s-until the beginning of the 1990s. Thereafter, they decreased through 2004, mainly driven by an inequality decrease at the lower tail of the distribution.

The slight decrease in the Q90-Q10 difference in the late 1970s, driven by a decrease in the Q50-Q10 difference, occurred during a period of strong increases in the minimum wage (the minimum wage

[11] student working periods are excluded.

is called *smic* for "salaire minimum de croissance") and unemployment (see Figure 2b). Conversely, the slight increase in the late 1980s, driven by an increase in the Q90-Q50 difference, occurred during a period of economic growth, characterised by falling unemployment and minimum wage stagnation. The decrease in the Q90-Q10 difference of log wages since the mid-1990s was due to a decrease in lower tail inequality, except for some stability at the end of the 1990s. In contrast, upper-tail inequality 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. The Gini coefficient draws a similar picture of the overall log wage inequality evolutions.

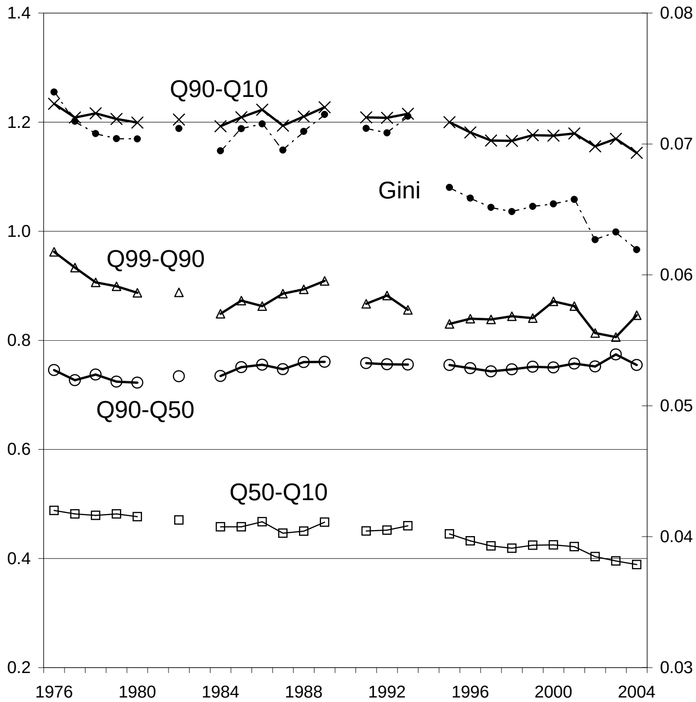
The Q99-Q90 log wage difference is also reported in Figure 2a to describe the top wage evolutions. Two recent French papers focus on a strong increase in the growth of top wages since the end of the 1990s. Amar (2010) and Landais (2008) show that the wage growth rate of wage earners above the Q99 has increased dramatically since the end of the 1990s. This event is likely to occur far beyond the top 1% of the wage distribution because the Q99 was fairly stable over 1976-2004. The Q99-Q90 difference decreased between 1976 and 1992 and remained quite stable between 1995 and 2004.[12]

The wage structure evolutions in France are very different from those observed in the United States and most other Western countries over the same period. For instance, in the U.S., the log of the Q90-Q10 weekly wage differences of full-time male workers increased by approximately 0.4 and the hourly log wage differences increased by approximately 0.2. The Gini coefficient (for annual earnings in commerce and manufacturing) increased from 0.4 to 0.5. After a period of increasing inequality at the top and the bottom of the wage distribution from 1975 to 1987, inequality remained stable at the bottom, whereas it continued to increase at the top until 2005 (see Goldin and Katz, 2007).

From 1976 to 2004, the composition of the French male labour force changed dramatically (see Figure 2c). From 1976 to 2004, the education level increased dramatically. Older workers, who were likely to be less educated, were gradually replaced by more educated baby-boomer cohorts. These trends are related to the succession of education policies during the 20th century. Two compulsory schooling laws increased the minimum school-leaving age: the age was raised in 1936 from 12-13 to 13-14 and was raised in 1959 from 14 to 16.[13] In addition, structural changes in the national educational system promoted the democratisation of education. From 1976 to 1989, the proportion of workers with basic vocational degrees increased from 30% to 40% due to a widening in access to basic education in the 1960s and 1970s. Since then, changes in labour force education have principally occurred through increasing shares of high school, advanced vocational and post-secondary degree holders. Once more, a political impulse led to these evolutions. In the mid-1980s, the government promoted the national objective of bringing 80% of cohorts to the baccalaureate level. A new vocational high school degree was created, the "Baccalauréat professionnel", which provided wider access to post-secondary education. The share of the labour force that attended college rose from 5% in 1985 to 12% in 2004, while the share that graduated from university increased from 4% to 10%. This composition was driven not only by demographic evolutions but also by labour market policies. The 1993 cuts in the social contributions of low wage earners contributed to the continuation of jobs with low qualifications, usually occupied by less educated people. The unemployment rate evolution also influenced the educational composition of the working labour force as more educated or more experienced people were less likely to be unemployed.

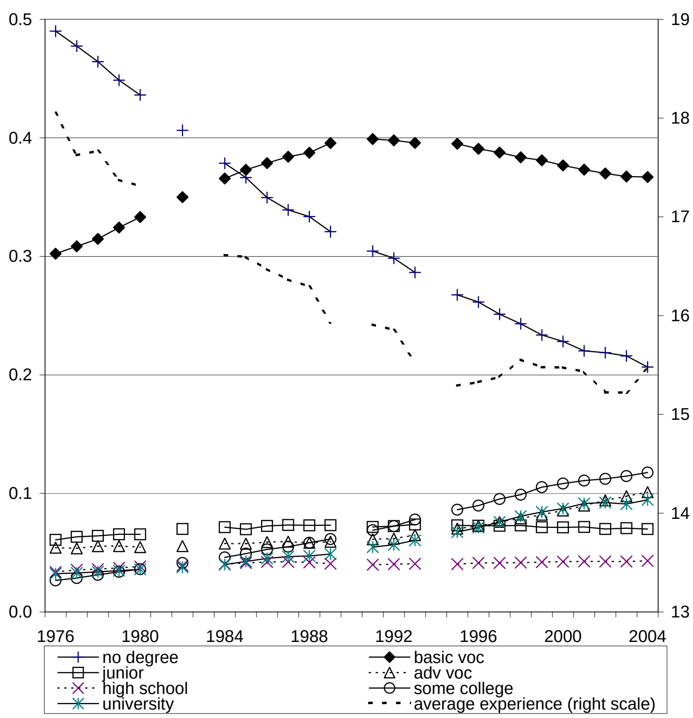
[12]More precisely, the increase in Q99 between 1996 and 2000 was stronger than the increase in Q90 and Q50. This is consistent with Amar (2010)'s findings: a stronger increase in Q99 than in Q50 over the period 1996-2007, with two main periods of growth in top wages, 1996-2000 and 2006-2007.

[13]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) Q90-Q10 differences and Gini coefficients for log wages

(b) Unemployment and minimum wage trends



(c) Education and experience trends

Figure 2: Inequality measures and labour market features

Figure 2b displays the experience trends. The average experience decreased from approximately 18 years in 1976 to 15.5 years in 1992 and it remained quite stable from 1995 to 2004. The decrease in experience before 1992 is partly due to the increase in the school-leaving age and to the fact that seniors left the labour market at younger ages following pension reforms in the early 1980s and some pre-retirement schemes. When controlling for age and education, the average level of experience was still much lower in 1992 than in 1976. This finding is related to the sharp increase in male unemployment from 2.8% in 1976 to 8.5% in 1993.[14]

Overall wage inequalities were fairly stable from 1976 to 1992 and decreased moderately from 1995 to 2004 due to a decrease in lower-tail inequality. However, the French labour market faced significant changes over the period, particularly regarding skill composition. To clarify the French wage inequality patterns, we control for these composition effects and disentangle between- and within-education group wage inequalities. We use quantile regressions on Mincer-type equations to focus on both tails of "residual" or within inequalities.

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 modelled 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;[15] exp_i denotes the experience as a wage earner in the private sector; and u_i is the error term. We proxy the educational attainment by degree dummies rather than by years of education, as is usually performed (see, among others, Martins and Pereira, 2004 and Lemieux, 2006a). This flexible specification relaxes the linear relation between the number of years of education and the corresponding between- and within-wage inequalities. We can therefore study more precisely the changes for different levels and types (vocational/non-vocational) of education.

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):

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

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

[15]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.

where $Q_y(\theta|dip, exp)$ denotes the $\theta-$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 a degree k and the $\theta-$quantile 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 this 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, these parameters cannot be interpreted as causal effects. In particular, no treatment is applied to account for possible endogeneity of the education and experience variables. Finally, as noted by Heckman et al. (2006), $\beta_{k\theta}$ cannot be interpreted as the internal rate of return of schooling but rather as the price of schooling from a hedonic market wage equation because the costs of education are not taken into account. For these reasons, we prefer to call 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.

The quantile regression model is estimated separately for each year between 1976 and 2004 at various quantile orders.[16] Quantile regression estimates for orders .10, .25, .50, .75 and .90 and for the years 1976, 1980, 1984, 1988, 1992, 1996, 2000 and 2004 are reported in Tables C.6 and C.7, together with corresponding OLS estimates. Standard deviations are obtained by a design matrix bootstrap Buchinsky (1998).[17]

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 the following:

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

where δ_θ is the slope parameter vector and x_i stands for the covariates appearing in equation (2) except the constant . If the true model is the homoskedastic location model (also simply called the 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 these two sub-models. We use simple Wald tests to test for a homoskedastic location model, as proposed by Koenker and Bassett (1982b) and Khmaladze-type tests based on the entire quantile process, as proposed by Koenker and Xiao (2002), to test both the location-shift and the location-linear in scale model hypotheses. We consider both the joint hypotheses and the univariate sub-hypotheses. For the Wald tests, the null hypothesis is equality of quantile parameters at the orders .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 used are those reported in Tables B.1. and B.2. (see 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 C.8 in the

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

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

appendix. The location-shift model is always rejected at 5% by Wald tests and by Khmaladze tests, whereas Khmaladze tests do not often reject the location-scale-shift model at 5%.

4.2. *Tools for the analysis*

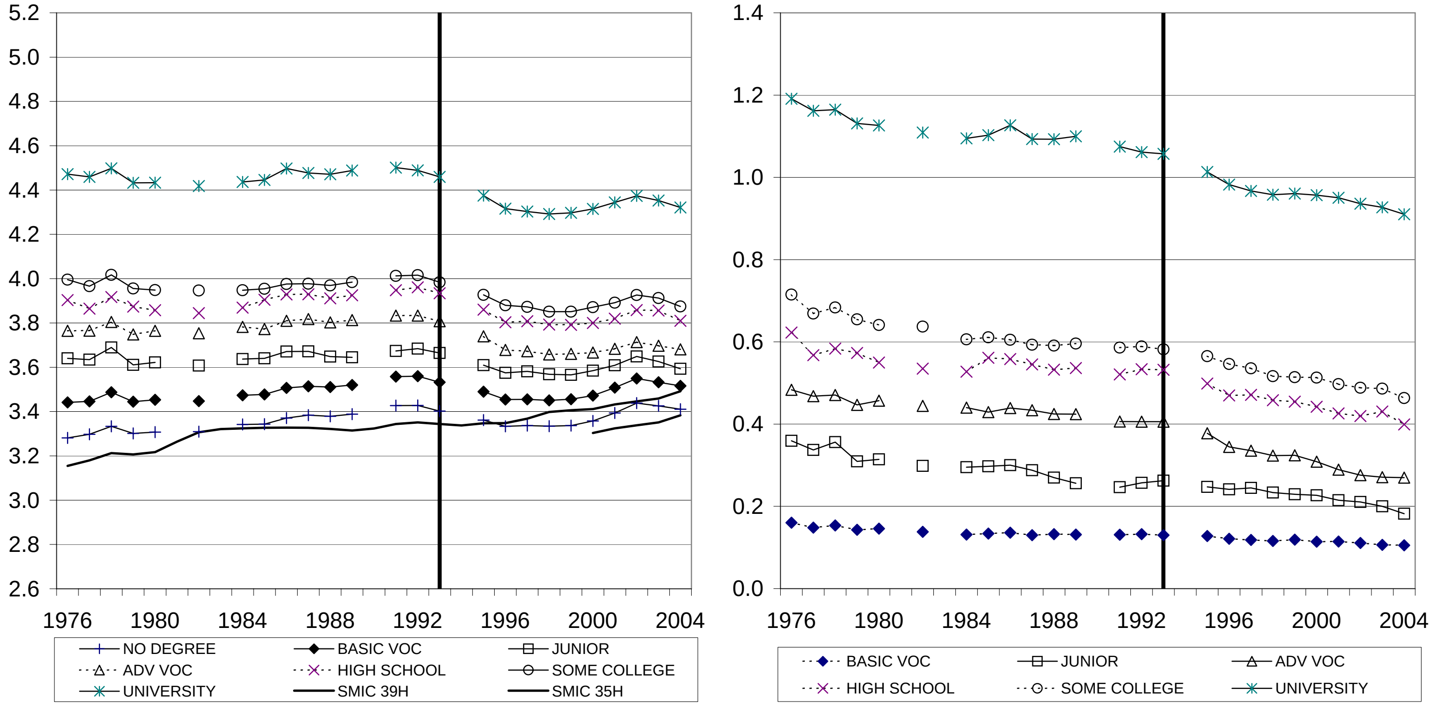
We exploit the quantile estimates to construct several descriptive tools. The education premium median (LAD) estimates are used to describe the between-education group inequalities, whereas the education premium quantile estimates at other orders provide information on within-education group inequalities. Similarly, the fitted values of the quantiles of the log wage conditional distribution (in short, the adjusted wage distribution) provide information on the within-wage inequality for a given education group, adjusted for experience. As within-inequality measures, we use Q90-Q10, Q50-Q10 and Q90-Q50 adjusted log wage differences. To emphasise what occurs at the middle of the distribution, we also compute adjusted Gini 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 following two sections, with graphical representations to emphasise evolutions. Wald tests are used to test whether those evolutions are significant, under an assumption of independence of the samples pertaining to two different years.

5. Decreasing wage inequalities within and between education groups

In this section, we show that the inequalities between and within education groups decreased over the period. We rely on wage estimates by education group and adjusted for experience (equation (2)).

5.1. *Between-education group inequalities*

Figure 3 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. The wages of each education group, adjusted for the level of experience, have a more or less procyclical component; see, for example, the great compression that occurred during the economic crisis of the mid-1990s. Beyond this cyclical part, the trends differ across the education groups. From 1976 to 1992, the adjusted log wages of the low-skilled and middle-skilled workers increased, whereas those of the more educated remained quite stable. Between 1995 and 2004, the adjusted log wages increased for the no degree and basic vocational degree groups, remained stable for the junior high school degree group and decreased for the more educated groups. The inequalities between education groups-adjusted for the level of experience-therefore decreased over the period. This decrease in between-education group inequalities can be observed by examining the degree premiums relative to no degree (see Figure 3b). The degree premiums decreased and became closer to each other over the period and the premiums of the more educated decreased the most. Because there could be endogeneity issues due to experience, we also ran an estimation with a third-order polynomial in age rather than experience (see Figure D.12a in the appendix) which provided a similar decrease in between-education group inequalities. Decreases in between-wage inequalities were stronger between 1976 and 1984 and between 1995 and 2004. From 1976 to 1984, unemployment and the minimum wage increased dramatically. In the same period, the share of the basic vocational degree group increased significantly, whereas the share of workers with no degree decreased inversely. From 1995 to 1998, unemployment was extremely high and since 1997, the minimum wage has increased dramatically. Finally, from 1995 to 2004, the share of highly educated workers increased.



(a) Q50 (LAD) adjusted log wages

(b) Q50 (LAD) premiums

Figure 3: Model (2): LAD premiums (relative to no degree) and median log wages adjusted for 0 years of experience.

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 4, 5 and 6 display the Q10, Q50 and Q90 log wages adjusted for experience (that is, computed with 0 years of experience) for the different degrees. Like overall wage inequalities, within-education group inequalities remained quite stable between 1976 and 1992 and decreased from 1995 to 2004, but the decrease in within-education group inequalities was much stronger. Before focusing on the overall evolution, we present some interesting general features of within-inequalities highlighted by our more flexible specification with diploma dummies rather than years of education.

Cross section

The adjusted wage inequalities are always higher for non-vocational degrees (university, high school and junior high school degrees) than for vocational ones.[18] Moreover, within a type of degree (vocational or non-vocational), the higher the education level, the higher the adjusted wage inequality. This result extends the analyses of Crépon and Gianella (1999) and Martins and Pereira (2004), who used the number of years of education as a proxy for the education level. They found that the higher the education, the greater the wage inequality. We find that this is true, but only if one controls for the type of education (vocational or general). For instance, the within junior high school group inequality is greater than that of the advanced vocational group. What happens at the tails of the wage distribution? For vocational

[18]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.

degrees, the within-group 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 because the strongest wage inequality at the top occurs for high school degrees.

Several factors may explain the increase in the within-group wage inequalities with the level of education. First, the degree category chosen may be increasingly heterogeneous as the level of education increases. For instance, the range of degrees included in the "university" category is probably larger than that contained in the "high school" category. Another explanation may be that the returns to unobserved components are more heterogeneous for higher levels of skills. Low-skilled workers may have jobs with pre-defined or repetitive tasks that do not permit them to reveal their abilities and for which wages are fixed. In contrast, high-skilled workers may be more autonomous, are more likely to be paid for performance (see Lemieux et al., 2009) and may have individual bargaining power. Martins and Pereira (2004), among others, maintain an over-education argument. Over-education is more likely to occur for high levels of education than is under-education for low levels. This imbalance may entail higher within-group inequalities for groups with higher education than for groups with lower levels. However, for Spain, Budría and Moro-Egido (2008) found that the positive association between post-secondary education and within-group earnings dispersion hinges on factors other than educational mismatch. As within-inequalities increase with the level of education, if the educational attainment of the labour force increases, then the overall dispersion of wages increases. Martins and Pereira (2004), Machado and Mata (2005) and Lemieux (2006b) highlighted the role of educational composition effects in the overall changes in inequality.[19] The enormous increases in educational attainment in France over this period obscured the decreasing trends that we observe in between- and within-education group inequalities. Moreover, unconditional mean wage and unconditional quantiles continually increased between 1995 and 2004, whereas the adjusted Q10, Q50 and Q90 log wage quantiles increased only for the less educated workers during this period. Consequently, most of the increase in average wages over the period resulted from increased levels of education. This finding 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. Therefore, our results remain compatible with additional changes in productivity that are unexplained by education but would have been captured by increases in social contributions over the entire period.

Evolutionary trends

The Q90-Q10 adjusted log wages differences were quite stable until the middle of the 1990s, as the evolution of the Q50-Q10 and the Q90-Q50 adjusted log wage differences compensated for each other. The within-education group wage inequalities slightly increased at the top (significant at the 5% level only for advanced vocational degrees), whereas they decreased slightly at the bottom (not significant at 5% for no degree, junior high school and advanced vocational groups).[20] The Q90-Q10 adjusted log wage differences decreased between 1995 and 2004 as both the Q90-Q50 and the Q50-Q10 decreased (not significant for high school and university degree holders). However, the decrease at the top principally occurred between 1995 and 1999 and was driven by a decrease of the Q90, whereas the decrease at the bottom occurred over the entire period. Decreases in the Q90-Q10 adjusted log wage differences were therefore higher between 1995 and 1999. The decrease in within-wage inequalities is also worth

[19]Note that Lemieux (2006b) uses a variance decomposition argument. Effects of a share increase for groups of education with higher within-inequalities on Q90-Q10 wage differences are less trivial. Autor et al. (2008) with another decomposition method focusing on upper and lower tail of the distribution find that the contribution of education composition effects to the increase in overall inequalities in the US is lower than the one measured by Lemieux (2006b) but still exists.

[20]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.

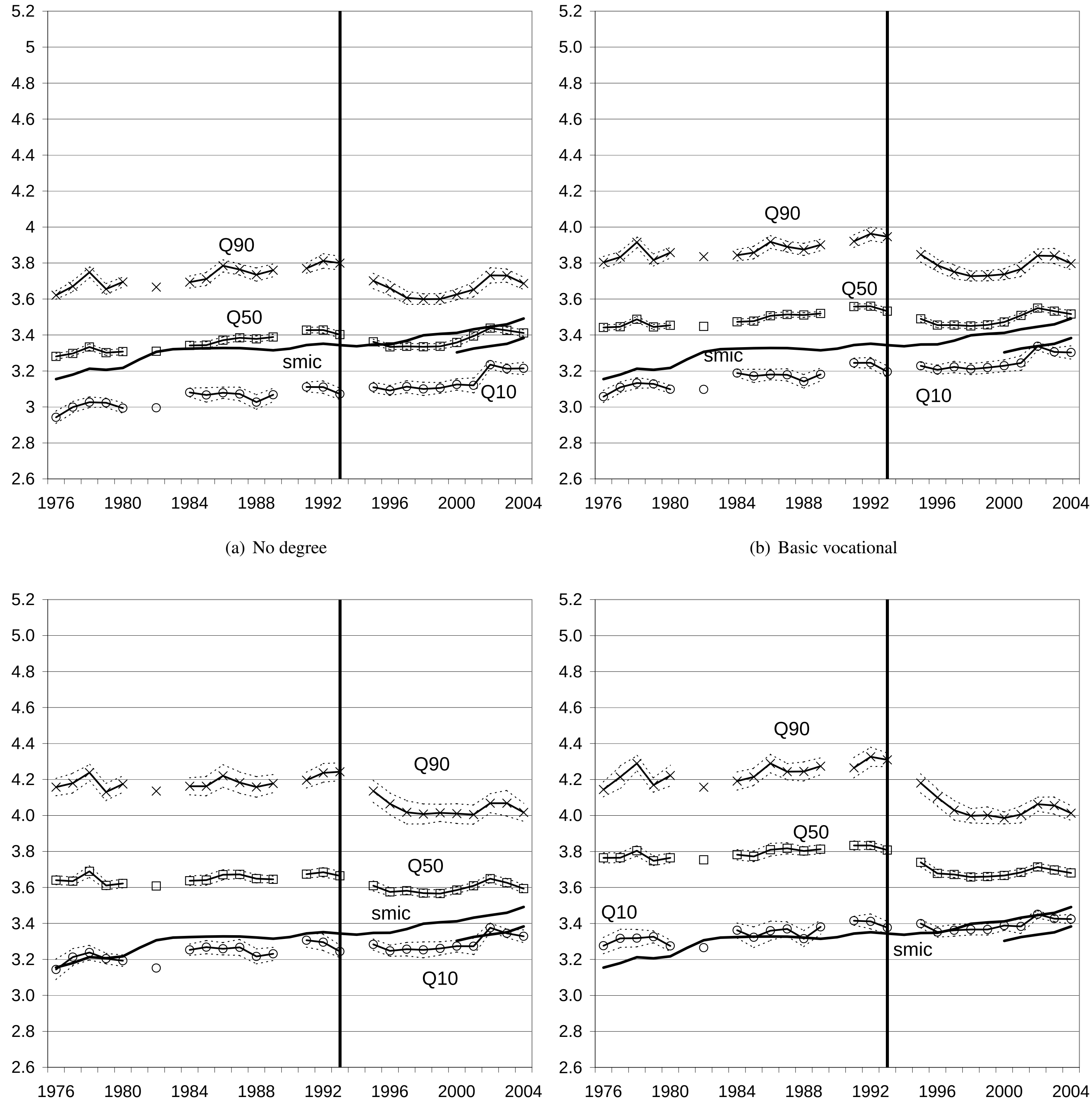
noticing in the evolution of the adjusted Gini coefficients as an alternative inequality measure (see Figure 6d). However, the decrease seems to be smoother between 1995 and 2004. The results for the specification with age rather than experience give similar conclusions (see Figure D.12b in the appendix). The evolution of the adjusted wage inequalities is stronger for the less educated workers.

Changes in within-inequalities are similar to those of overall wage inequalities but are much stronger. The decline of the unconditional Q90-Q10 log wage differences between 1995 and 2004 was approximately 0.07, or a 6% decrease. The stronger decrease of the "conditional or within" Q90-Q10 adjusted log wage differences (i.e. for the no diploma workers) was approximately 0.1, or 17%.

5.3. Is the minimum wage a defence against increasing inequality?

Minimum wage trends seem to provide a compelling explanation for decreases of between and within inequalities. The between-education group wage inequalities decreased mainly between 1976 and 1984 and from 1995 to 2004. A large part of this decrease came from increasing wages of less educated workers during periods of minimum wage hikes. Less educated workers are likely to be paid less and to be more affected by minimum wage increases. On the whole period, the minimum wage increased 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 that of the minimum wage, except for the period 1995-1998 (see Figure 3)a. Between 1976 and 1983, the minimum wage increased dramatically, particularly in 1981 and 1982, when the government increased it markedly above the level automatically predicted by the legislation ("coup de pouce"). As a result, in 1982, 7.8% of workers with no degree and 3.5% of university degree holders were paid at the minimum wage. A significant slowdown occurred between 1983 and 1996 and the minimum wage remained roughly stable, except for an increase between 1989 and 1992. Since 1997, when another "coup de pouce" occurred, the minimum wage has increased again (Carcillo and Delozier, 2004). Further, the legal working time reduction from 39 hours to 35 hours per week, which was introduced in 1998, was accompanied by a significant hourly minimum wage hike. Because the new working time was not applied in every firm on the same date, a significant number of workers remained at 39 hours and saw their monthly wages increase (see Koubi and Lhommeau, 2007). Periods of significant increase in the minimum wage are thus concomitant with large declines in between-education group wage inequalities. Furthermore, the decreases in education premiums ended first for the basic vocational group, who had lower wages; the higher minimum wage probably caught up the level of their wages earlier than for other groups. Minimum wage increases also provide a compelling explanation for the stronger decrease in within-inequalities for the less-educated workers and the decreasing trend in lower-tail inequality over the period, regardless of educational level. The minimum wage may tighten the bottom of the wage distribution through several channels. Firstly, workers with productivity lower than the minimum wage are not employed. Secondly, the minimum wage prevents firms from pushing down wages for workers with low bargaining power and thus reduces the heterogeneity at the bottom. Thirdly, a minimum wage increase entails an increase in wages for workers paid at the minimum wage level, a weaker increase for workers whose wages are slightly above the minimum wage (spill-over effects) and little or no effect on high-paid workers. Lastly, "low-wage traps" may have occurred after the 1990s, in which firms have been encouraged to hire at the minimum wage to benefit from exonerations.

Unemployment could also explain part of our results. Its selection effect is likely to shift to the right the distribution of unobserved skills and, consequently, wages. Moreover, unemployment can entail wage compression as a high level of unemployment puts pressure on wages. Some facts are consistent with unemployment pressure on wages. Unemployment of less educated workers increased between 1976 and 1984 (see Figure D.10a in the appendix), when education premiums declined sharply. Unemployment was extremely high in the mid- to late 1990s, over 8% between 1993 and 1999 (see Figure 2b), the



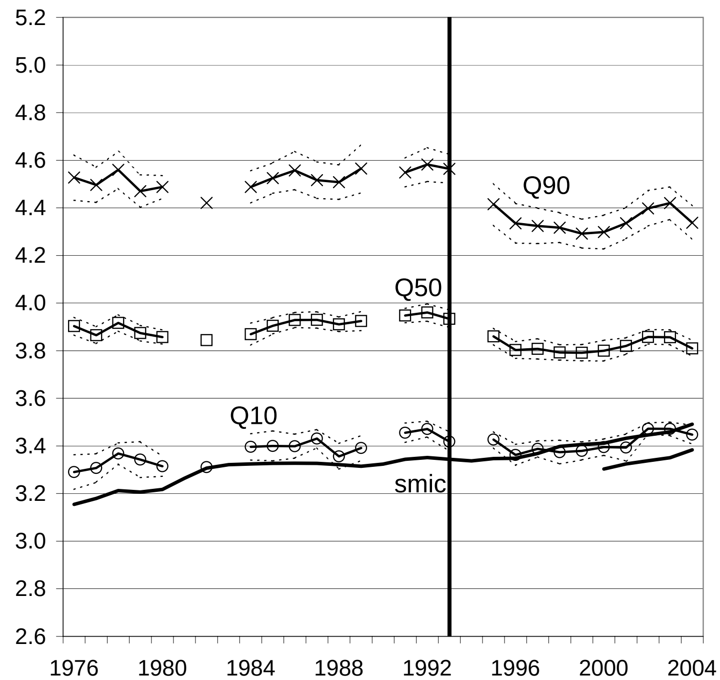
(a) No degree

(b) Basic vocational

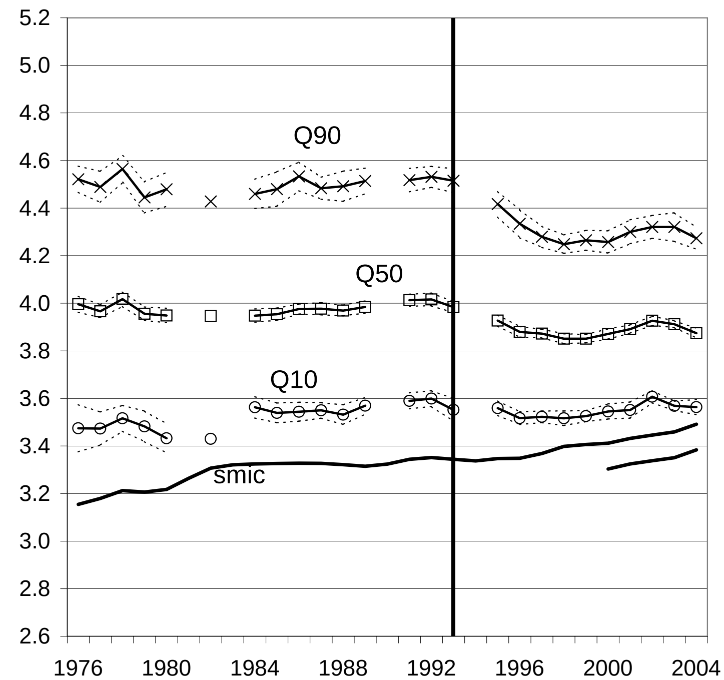
(c) Junior high school

(d) Advanced vocational

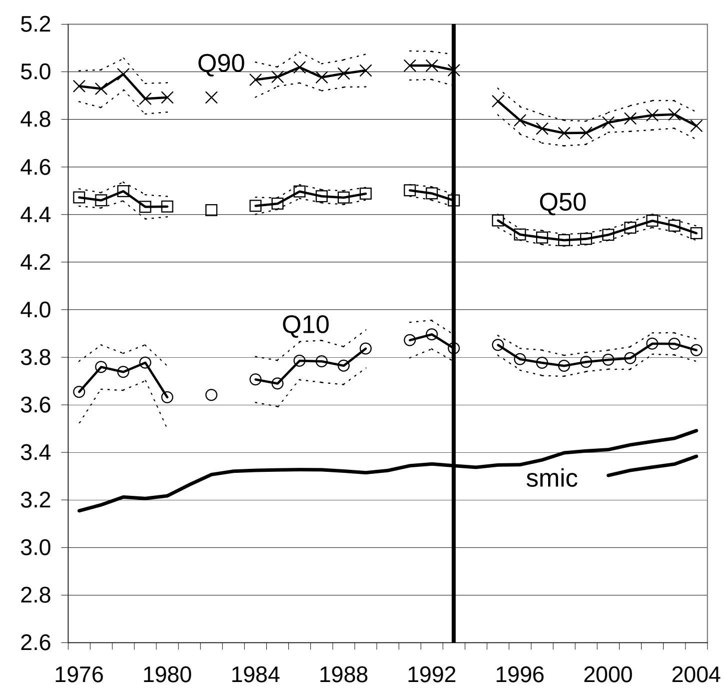
Figure 4: Model (2): Q10, Q50 and Q90 log wages adjusted for 0 years of experience (1).



(a) High school

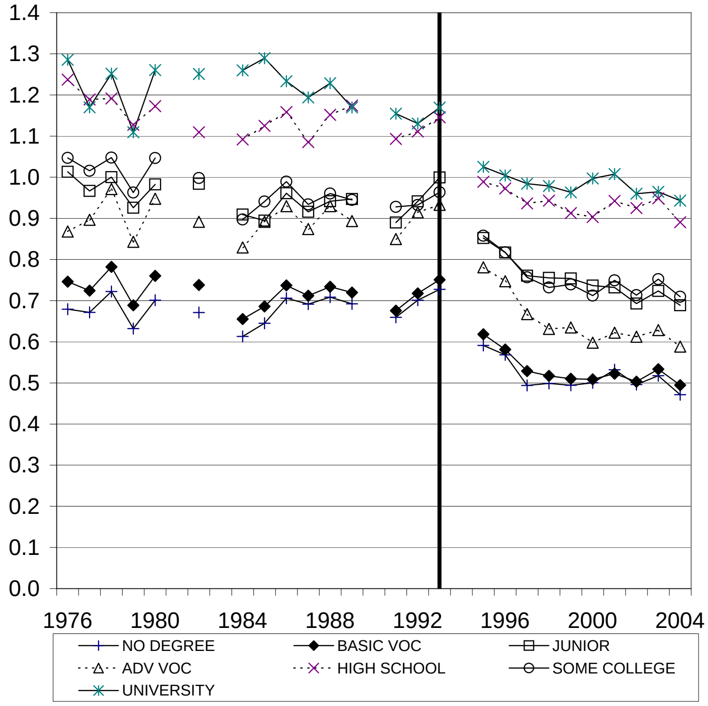


(b) Some college

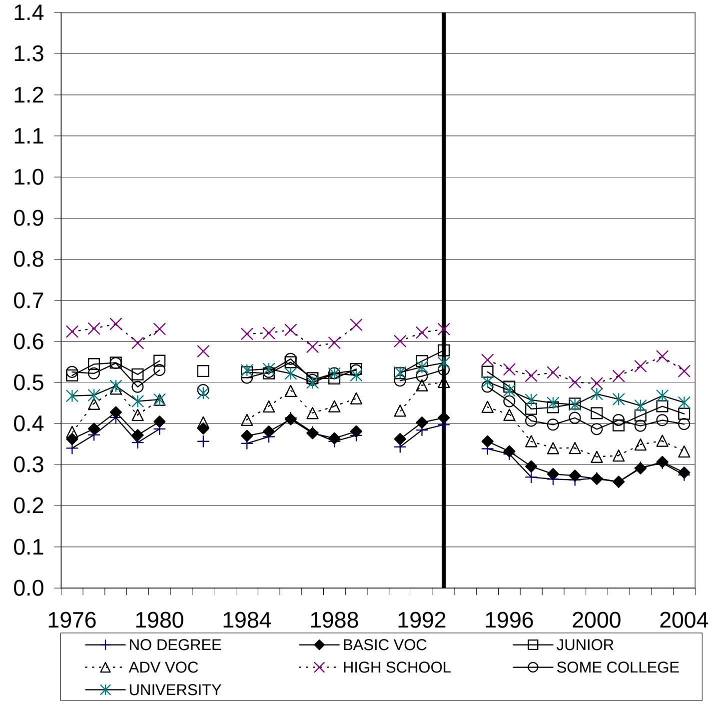


(c) University

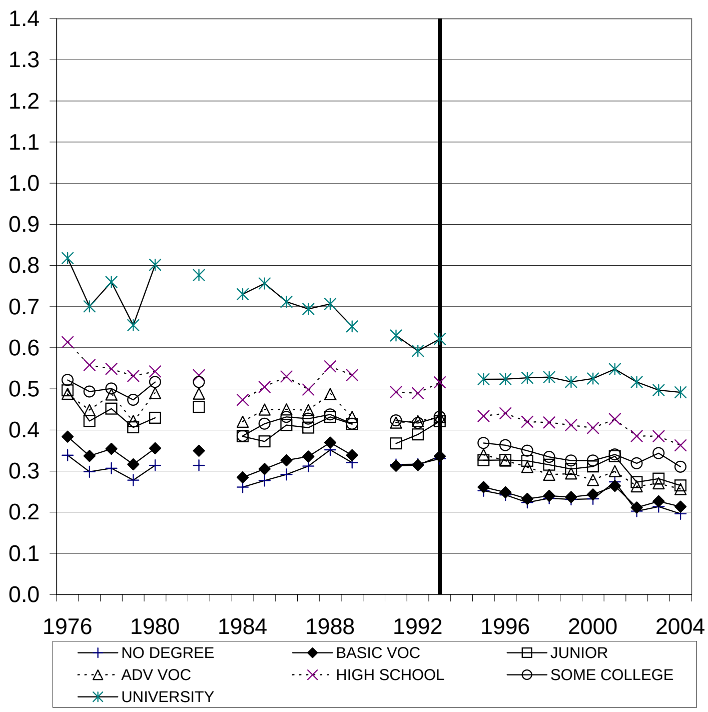
Figure 5: Model (2): Q10, Q50 and Q90 log wages adjusted for 0 years of experience (2).



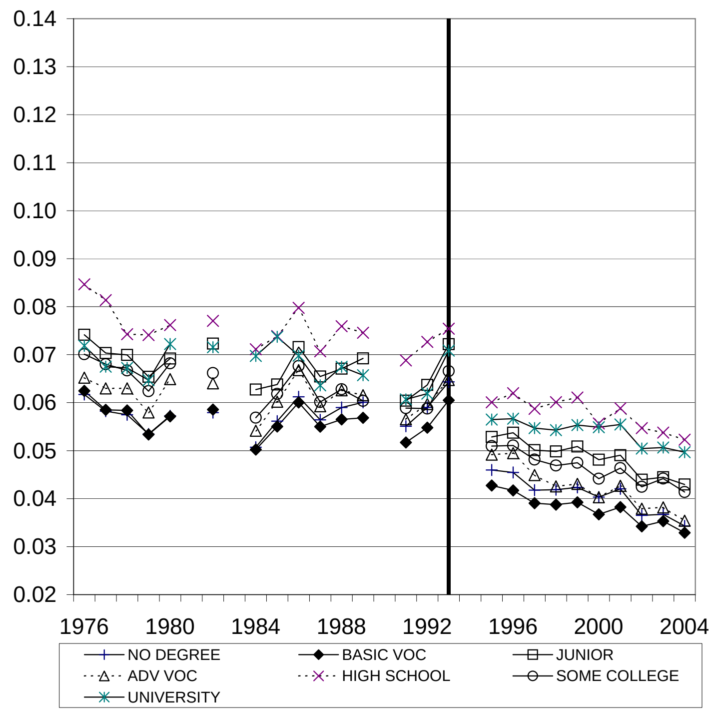
(a) Q90-Q10 log wages differences



(b) Q90-Q50 log wages differences



(c) Q50-Q10 log wages differences



(d) Gini coefficients

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

only period of declining upper-tail residual inequalities. Yet, the stability of the Q10 and Q50 for the less educated workers from 1995 to 1999 casts doubt on the existence of a selection effect. A more convincing explanation is that unemployment and minimum wage effects 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 factor could explain why the decline in upper tail was stronger for the less educated workers: only the adjusted Q90 decreased for them, not both the adjusted Q90 and Q50.

A third potential explanation for our findings is the increase in educational attainment over the period. The fall in skill premiums could be due to a classic supply and demand effect: the increase in labour demand did not compensate for the increase in labour supply of skilled workers. The fact that the increases in degree share and the decreases in education premiums occurred at the same time supports this explanation, especially for secondary and post-secondary degrees (see Figure 2c). The U.S. has experienced similar patterns in the past. Goldin and Katz (2007) found that the narrowing of the U.S. wage structure between 1910 and 1950 caused by decreasing education premiums was linked to a sharp increase in educational attainment. The increase in secondary and post-secondary educational attainment could also have entailed an increase in 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 is lower for the higher degrees between 1995 and 2004.

To disentangle these three potential explanations, we rely on correlations between inequalities (between and within) and the minimum wage, unemployment and education supply. Specifically, we first regress the university premium relative to no degree on current minimum wage, unemployment and the relative share of university degree-holding workers with respect to workers with no degree. We compute this share each year using the Labour Force Surveys and taking into account both men and women. We only focus on the university premium relative to no degree because this is the strongest premium and all premiums decreased over the period. This type of regression is similar to the ones derived from a production function in the literature (see Katz and Murphy, 1992 or Autor et al., 2008, for example). To compare our results to the previous results presented in the literature, we also include a trend in one specification, which captures changes in the demand for high-skilled workers. A positive coefficient is interpreted as a sign of skill-biased technological change. Note, however, that recent papers on job and wage polarisation emphasise the ambiguous effects of technological change, which may affect the employment and wages of medium-skilled workers but not low-skilled workers. Minimum wages variations seem to be the main force driving the decline in between-inequalities (see Table 1). The supply variable has a negative coefficient that increases when including the time trend but is not statistically significant.[21] This could be partly due to the fact that variables are strongly correlated and lead to imprecise estimations.

We run similar regressions on within-inequalities for each education group. The supply variable is now the log of the share of workers with the same diploma. The expected effect of this latter is unclear. An increasing share of a given degree owners can be correlated with higher heterogeneity in unobserved skills and therefore to higher within inequalities. But it can also entail higher competition between workers of this group and thus exerts a downward pressure on wages. Unemployment effects are also ambiguous. Selection effect would reduce within-inequalities but pressure on wages effects depend on what part of the distribution is affected and to what extent. We again find a strong negative effect of minimum wage – except for high-school and university degree owners. Residual wage dispersion of university degree owners does not seem to be affected by the minimum wage. It is not surprising as

[21] Verdugo (2011) runs similar regressions. For the university on less than high school wage gap, the supply and demand effects are not significant when including the minimum wage in the regression.

Table 1: University premium relative to no degree

Male unemployment rate	0.003 (0.002)	0.003 (0.002)
Relative supply of education	-0.031 (0.027)	-0.065 (0.1)
Minimum wage	-0.337^{**} (0.138)	-0.349^{***} (0.135)
Time trend		0.003 (0.007)

***: p-value$<$ .01, **: p-value$<$ .05, *: p-value$<$ .1. Bootstrapped standard errors obtained with 50 replicates are reported in parentheses. Intercept and a dummy to control the data break after 1993 are included. Relative supply is the log of the number of men and women in the labour force with an education level divided with those with no degree Minimum wage is in log of real daily wage (39 hour per week reference)

this degree is mainly composed of high-paid workers. We find positive effects of unemployment for both specifications for no degree and advanced vocational and no effect in both specifications for junior high-school, some college and university degrees. These findings are hard to interpret. Unemployment pressure on wages and selection effects could cancel out each other, or pressure on wages could be the same on Q10 and Q90. Yet, the positive effect on no degree owners workers is challenging, as the wage of these workers is binded by the minimum wage.

Table 2: Adjusted Q90-Q10 log wage difference

	No degree		Basic vocational		Junior high school		Advanced vocational	
Male unempl.	0.02^{***} (0.005)	0.019^{***} (0.007)	0.012^{**} (0.006)	0.013 (0.008)	0.013 (0.008)	0.012 (0.009)	0.031^{***} (0.005)	0.029^{***} (0.005)
Education supply	-0.14 (0.096)	-0.073 (0.346)	0.13 (0.141)	0.121 (0.266)	0.316 (0.204)	0.298 (0.201)	-0.033 (0.075)	-0.14 (0.095)
Min. wage	-0.555^{**} (0.223)	-0.579^{**} (0.261)	-0.387^{***} (0.096)	-0.401 (0.382)	-0.517^{***} (0.18)	-0.728^{**} (0.33)	-0.616^{***} (0.211)	-0.879^{***} (0.311)
Time trend		0.002 (0.012)		0 (0.006)		0.003 (0.004)		0.008 (0.005)

	High school		Some college		University	
Male unempl.	0.023^{**} (0.01)	0.011 (0.013)	0.01 (0.007)	0.011 (0.009)	0.011 (0.009)	0 (0.01)
Education supply	0.21 (0.208)	-0.017 (0.234)	0.11 (0.102)	0.063 (0.213)	0.001 (0.177)	1.524^{**} (0.647)
Min. wage	-0.39 (0.24)	-1.085^{***} (0.353)	-1.033^{***} (0.314)	-1.053^{***} (0.323)	-0.238 (0.573)	-0.088 (0.592)
Time trend		0.012^{*} (0.006)		0.002 (0.008)		-0.063^{**} (0.028)

***: p-value$<$ .01, **: p-value$<$ .05, *: p-value$<$ .1. Bootstrapped standard errors obtained with 50 replicates are reported in parentheses. Intercept and a dummy to control the data break after 1993 are included. Relative supply is the log of the share of the labour force with this education level. Minimum wage is in log of real daily wage (39 hour per week reference)

6. The decreases of within- and between-education group wage inequalities are driven by the less experienced workers

We analyse if the previous results derived from the Mincer specification (equation (2)) are driven by some levels of experience. We therefore considere an alternative specification, in which degree dummies and experience are interacted. Effects of experience are allowed to be heterogeneous by education groups. This enables us to study the evolutions of within- and between-education group wage inequalities at different levels of experience. Specifically, we considere

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

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 C.9, C.10, C.11, C.12, C.13 and C.14 in the appendix. OLS estimates are also reported. Tables C.15 and C.16 contain the inference results. The location-shift model are 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 1990s.

Model (4) accounts for the non-separability of the two human capital types, i.e. education and experience.[22] Workers who are more educated usually receive training opportunities and promotions more easily and they may be able to acquire or use skills faster than others. This may be related to unobserved education group abilities or to an indirect effect of education. Again, we do not to identify a causal effect of education. We describe how different education-group-rewarding profiles of experience affect education-group wage heterogeneities and above all we study how these profiles have changed since the 1970s.

6.1. Between-education group inequalities

Figure 7 displays the LAD adjusted log wages for the different education groups at 0, 3, 10 and 30 years of experience. Between-education group wage inequalities increase with the level of experience, regardless of the year. In other terms, apparent experience-rewarding profiles are higher for the more educated workers. To compare these experience-rewarding profiles, we report the LAD estimates of the marginal effects of experience by education groups for 1976 and for 2004; see Figure D.11 in the appendix. We find decreasing returns to experience both in 1976 and in 2004. Moreover, the returns to experience increase with education, at least until 10 years of experience.

Once allowing for different education-group rewarding profiles of experience, it appears that the 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 holders. In other words, education had a directly positive impact on hiring wages in the 1970s and the 1980s, but this effect disappeared at the beginning of the 1990s – except for university degree holders. Since then, the channel through which the education affects the wages has been closely related to the experience-rewarding profile and the experience accumulation process.[23]

The compression of wages is worth noticing for 0 but also for 3 and 10 years of experience. On the one hand, the adjusted wages of the less educated groups increased over the period. They increased similarly than the minimum wage, particularly for the lowest levels of experience. On the other hand, the adjusted wages of the more educated decreased, sharply between 1976 and 1984 and since 1995. This convergence entailed a decrease in between-education group inequalities over time. The wages at 30 years of experience are rather stable between 1976 and 1995 but a weak convergence appears since

[22]see Rubinstein and Weiss (2006); Belzil (2006); Heckman et al. (2006).

[23]The break in the data in 1993 and border effects can also partly drive our results. However results on other French data confirm that education has a lower effect on hiring wages over time.

the 2000s. The between-education group inequalities decline that we previously analysed is thus not homogeneous across experience groups. It is mainly driven by a decrease in between-inequalities for the less experienced workers.

6.2. Within-education group inequalities

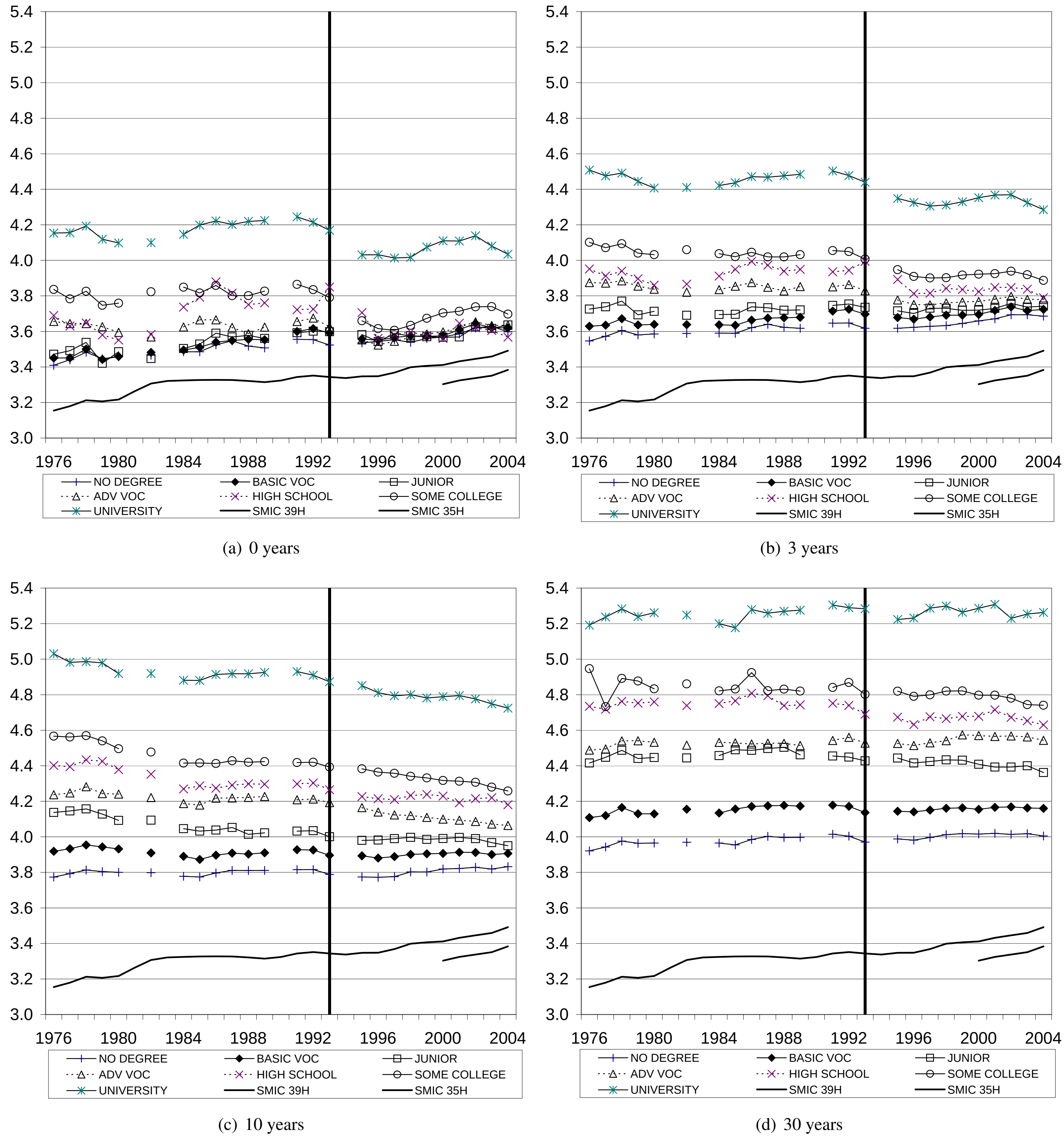
Like between-education group inequalities, within-education group inequalities are mainly driven by changes for the less experienced workers. Within-education group inequalities were quite stable between 1976 and 1992 and decreased since 1995, see Figure 8. Decreases are stronger for the less experienced – and the less educated – workers. Results are similar when looking at Gini coefficients, see Figure 9.

6.3. The stronger decrease in inequalities for the less experienced workers can also be explained by the minimum wage rise

This new specification highlights some features of wage inequalities. 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. These higher returns can be due to experience or to seniority. If 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 workers, unemployment pressure on wages and the "low-wage trap" reduce the wage differentials between different levels of experience. Moreover, mobility is more likely to be a negative signal for those workers, because it is more often involuntary (end of short-term contracts for example).

Concerning evolutions, the decrease in between-wage inequalities is stronger for the less experienced workers. This feature is consistent with minimum wage and unemployment explanations : the less experienced workers are more often paid at the minimum wage and more likely to be unemployed. The education supply effect is also a possible candidate: the competition on the labour market is probably stronger among people with similar levels of experience and the new college and university graduates are less experienced. Concerning within-inequalities, the decrease is also stronger for the less experienced workers. Once more, there is no "unicausal" explanation.

We run regressions in an attempt to disentangle the contributions of the different explanations. We focus on 3 and 10 years of experience. We use the same explanatory variables as previously but we also add a measure of the "effective competition" that a worker could experience from an increase in the share of workers with the same level of education. We therefore compute the relative experience which is the difference between the experience level of the worker and the mean experience level of people with the same level of education. Concerning between-inequalities, we only focus on the higher premium, the university premium relative to no degree. As previously, only the minimum wage seems to play a role in decreasing education premiums, see Table 3 . As mentioned before, these results need to be treated with caution. Concerning within-inequalities, the minimum wage has a stronger effect at 3 years than at 10 years of experience, see Table 4. At 10 years the coefficient is not statistically significant for junior high-school, some college and university degree owners. This is consistent with the fact that the minimum wage mostly impacts the low-paid workers. For some degrees, unemployment has a positive and statistically significant effect on within-inequalities. In most of the regressions, the coefficients of education and experience supplies are non statistically significant. These results therefore favour the minimum wage explanation and the results on unemployment are puzzling.



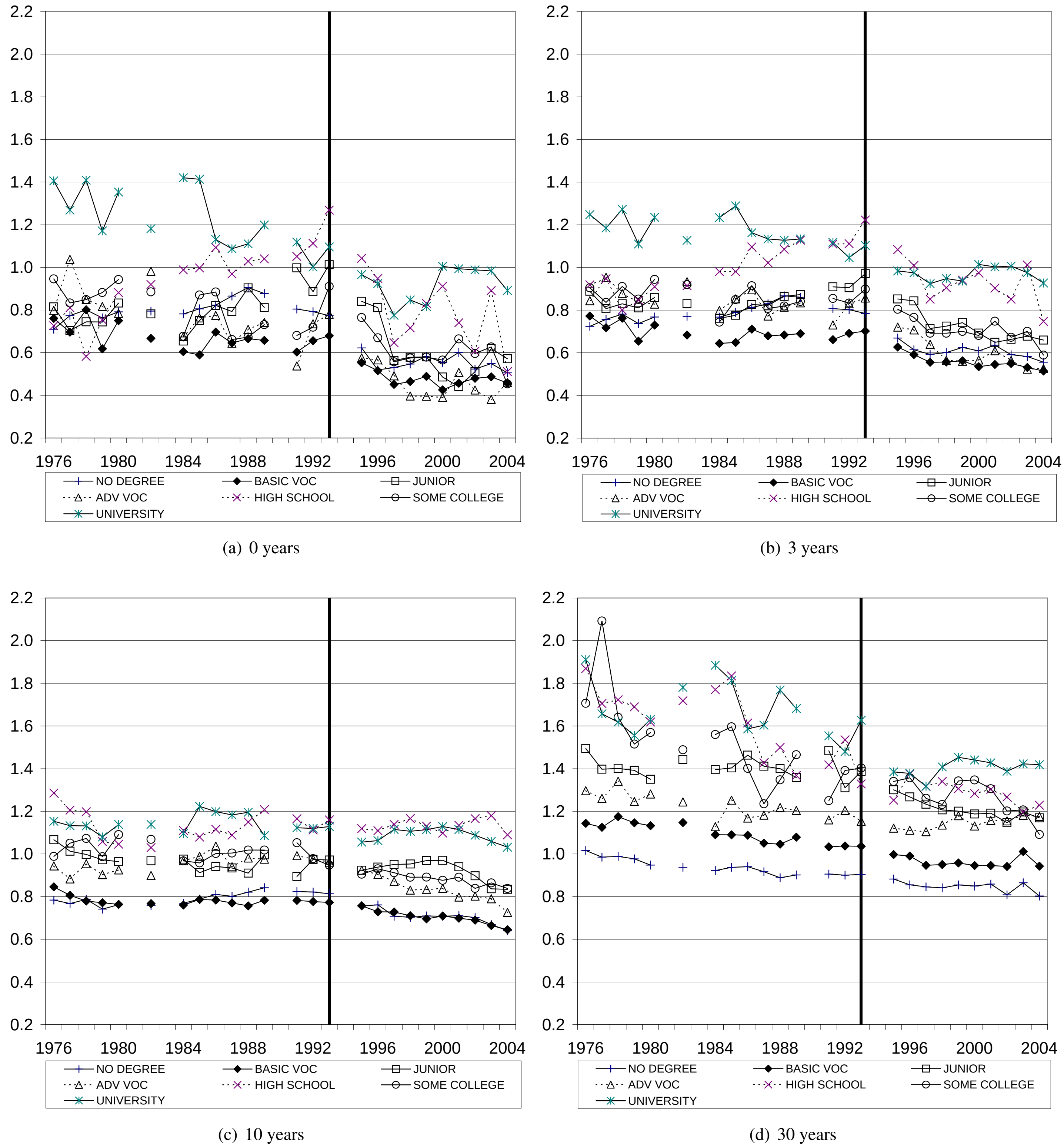
(a) 0 years

(b) 3 years

(c) 10 years

(d) 30 years

Figure 7: Model (4): LAD-median log wages estimates at various levels of experience.



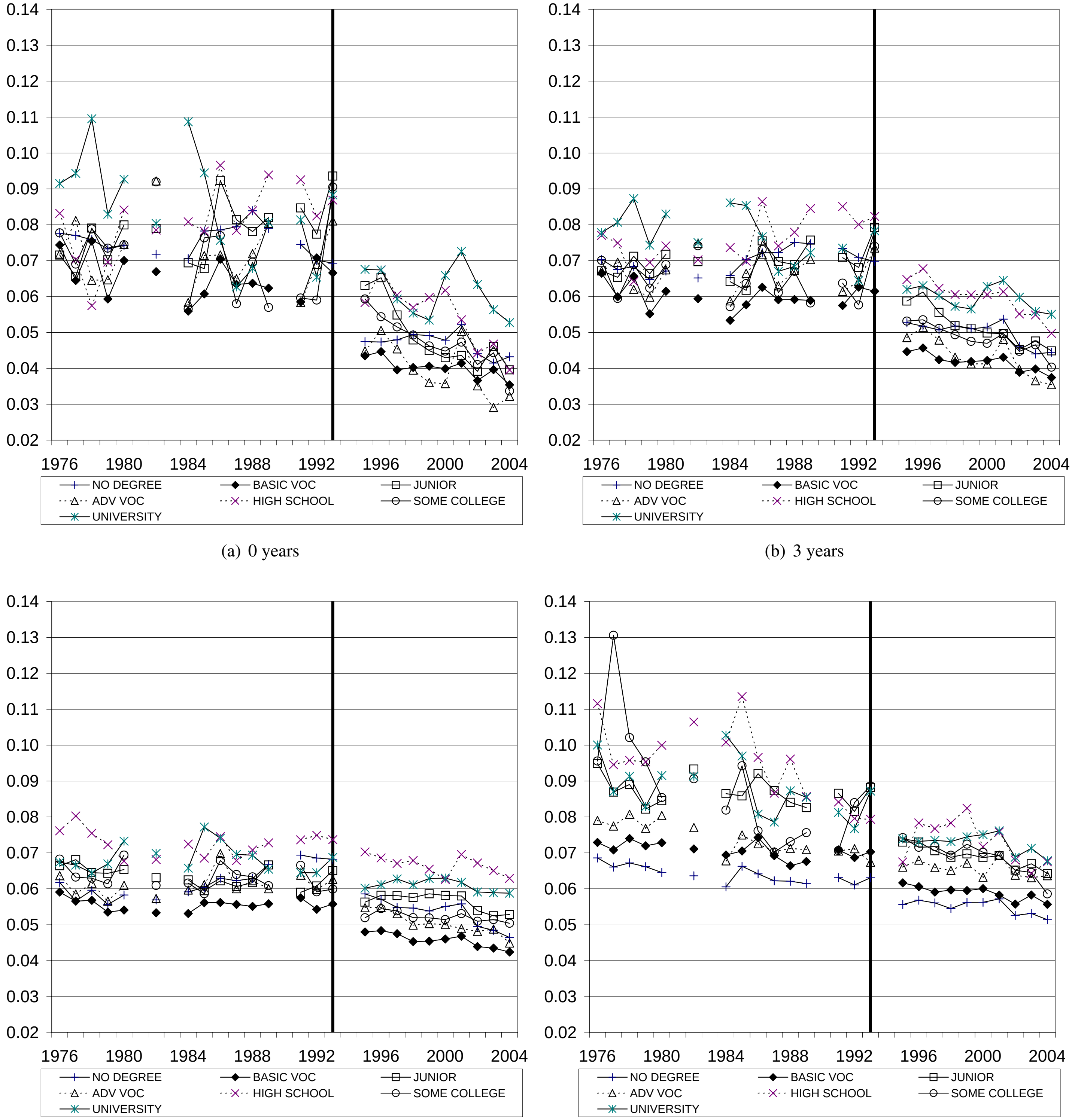
(a) 0 years

(b) 3 years

(c) 10 years

(d) 30 years

Figure 8: 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 9: Model (4): Gini coefficients of log wage distributions adjusted for various levels of experience.

Table 3: University premiums relative to no degree at 3 and 10 years of experience

	3 years of experience		10 years of experience	
Male unemployment rate	-0.002	-0.001	0.005	0.006
	(0.005)	(0.005)	(0.004)	(0.004)
Relative supply of education	0.075^{*}	-0.131	-0.005	-0.13
	(0.043)	(0.22)	(0.033)	(0.229)
Relative experience	-0.016	0.016	-0.011	0.01
	(0.012)	(0.017)	(0.009)	(0.017)
Minimum wage	-0.85^{***}	-0.907^{***}	-0.738^{***}	-0.772^{***}
	(0.236)	(0.252)	(0.187)	(0.195)
Time trend		-0.005		-0.004
		(0.018)		(0.014)

***: p-value$< .01$, **: p-value$< .05$, *: p-value$< .1$. Bootstrapped standard errors obtained with 50 replicates are reported in parentheses. Intercept and a dummy to control the data break after 1993 are included. Relative supply is the log of the number of men and women in the labour force with an education level divided with those with no degree Relative experience is the difference between the experience level studied and the mean experience level of people with the same level of education. Minimum wage is in log of real daily wage (39 hour per week reference)

Table 4: Adjusted Q90-Q10 log wage differences at 3 and 10 years of experience

	No degree				Basic vocational			
	3 years of experience		10 years of experience		3 years of experience		10 years of experience	
Male unempl.	0.03***	0.025**	0.019***	0.013**	0.002	0.003	0.002	0.004
	(0.005)	(0.012)	(0.003)	(0.007)	(0.006)	(0.006)	(0.003)	(0.004)
Education supply	−0.222	0.144	−0.17**	0.21	0.1	−0.003	0.282***	0.154
	(0.149)	(0.652)	(0.068)	(0.331)	(0.169)	(0.203)	(0.089)	(0.14)
Experience supply	−0.042**	−0.036	0.003	0.009	0.004	0.009	0.023***	0.03*
	(0.021)	(0.027)	(0.011)	(0.014)	(0.011)	(0.013)	(0.008)	(0.01)
Min. wage	−0.854*	−0.876*	−0.612***	−0.635***	−0.44**	−0.611**	−0.23*	−0.444**
	(0.514)	(0.504)	(0.218)	(0.213)	(0.184)	(0.241)	(0.124)	(0.196)
Time trend		0.013		0.013		0.004		0.005
		(0.021)		(0.011)		(0.005)		(0.004)

	Junior high school				High vocational			
	3 years of experience		10 years of experience		3 years of experience		10 years of experience	
Male unempl.	0.02	0.02	−0.002	−0.002	0.023***	0.022**	0.033***	0.032***
	(0.015)	(0.015)	(0.01)	(0.01)	(0.008)	(0.009)	(0.007)	(0.007)
Education supply	0.442	0.277	0.375	0.253	0.008	−0.063	−0.088	−0.137
	(0.329)	(0.345)	(0.275)	(0.301)	(0.153)	(0.147)	(0.112)	(0.101)
Experience supply	−0.045**	−0.008	0	0.027	0.006	0.009	0.002	0.004
	(0.022)	(0.028)	(0.017)	(0.025)	(0.026)	(0.026)	(0.025)	(0.024)
Min. wage	−1.365***	−1.673***	−0.623*	−0.849**	−0.949**	−1.104**	−0.451	−0.559
	(0.443)	(0.479)	(0.372)	(0.412)	(0.396)	(0.537)	(0.299)	(0.392)
Time trend		0.015*		0.011		0.005		0.003
		(0.008)		(0.007)		(0.008)		(0.005)

	High school				Some college			
	3 years of experience		10 years of experience		3 years of experience		10 years of experience	
Male unempl.	0.045**	−0.025	0.025*	−0.035*	0.003	0.005	−0.002	−0.005
	(0.02)	(0.027)	(0.015)	(0.02)	(0.011)	(0.012)	(0.011)	(0.01)
Education supply	0.114	−1.417***	0.358	−0.959**	0.165	0.06	−0.099	0.062
	(0.392)	(0.531)	(0.277)	(0.408)	(0.141)	(0.367)	(0.153)	(0.361)
Experience supply	0.011	0.163***	−0.017	0.114**	0.004	0.001	−0.03	−0.026
	(0.039)	(0.055)	(0.028)	(0.048)	(0.029)	(0.033)	(0.037)	(0.042)
Min. wage	−0.008	−1.437*	−0.896*	−2.125***	−1.163**	−1.224**	−0.523	−0.43
	(0.74)	(0.817)	(0.478)	(0.545)	(0.456)	(0.531)	(0.372)	(0.455)
Time trend		0.063***		0.054***		0.005		−0.007
		(0.016)		(0.013)		(0.015)		(0.014)

	University			
	3 years of experience		10 years of experience	
Male unempl.	−0.008	−0.02	−0.012	−0.018
	(0.014)	(0.017)	(0.011)	(0.014)
Education supply	−0.34	0.8	0.027	0.559
	(0.234)	(1.238)	(0.229)	(0.824)
Experience supply	0.003	−0.013	−0.032	−0.04
	(0.045)	(0.046)	(0.04)	(0.042)
Min. wage	0.817	0.924	−0.227	−0.177
	(0.68)	(0.699)	(0.69)	(0.717)
Time trend		−0.048		−0.022
		(0.052)		(0.035)

***: p-value$<$ .01, **: p-value$<$ .05, *: p-value$<$ .1. Bootstrapped standard errors obtained with 50 replicates are reported in parentheses. Intercept and a dummy to control the data break after 1993 are included. Relative supply is the log of the share of the labour force with this education level. Relative experience is the difference between the experience level studied and the mean experience level of people with the same level of education. Minimum wage is in log of real daily wage (39 hour per week reference) Computations on the the labour force using the French labour force survey

7. Sensitivity analysis

We run several alternative specifications to check the sensitivity of our results. The results presented for both specifications hold regardless of the robustness check implemented.[24] 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 excluded as student working periods. Therefore, we consider an alternative specification in which the education variable contains an additional category for students, "in studies". Because we do not distinguish between experience accumulated while working during studies and experience accumulated after studies, we also consider experience accumulated only after the end of the studies. Pension reforms, pre-retirement schemes and increasing senior unemployment could drive part of our results. We run the two specifications on a restricted sample with only the 15-to 54-year-old workers. Finally, 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.

8. Concluding remarks

In this paper, we document a decrease in both between- and within-education group wage inequalities over a thirty-year period in France. These decreases are mainly driven by decreases in education premiums and "residual" inequalities for the less experienced workers. We do not find any increase in returns to education or in upper-tail inequalities, at least until the top 1% of the wage distribution. The main force that seems to drive these changes is the minimum wage increase over the period. Supply and demand effects and unemployment pressure on wages could also have played a role notably in the stability of upper-tail inequalities, but the evidence is less clear. The results in France favour non-market explanations and do not provide further evidence of skill-biased technological change. While the literature documents international evidence on skill-biased technological changes since the 1980s, we find that institutional factors are consistent with the divergent trends observed in France and in the U.S., so country particularities must be taken into account. In particular, workers in France are less often paid for performance and the share of the financial sector in high-paid workers' employment is lower than in the U.S. or the U.K..

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Appendix 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.

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 in the 1990 and 1999 censuses and the annual census surveys 2004-2006. 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. In the 1990 and 1999 censuses and the annual census surveys 2004-2006, individuals were only 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).[25] In order to check that this imputation does not affect the results, we consider some alternatives in the sensitivity analysis section.

Education variable. We use the EDP information to construct the highest degree obtained once studies completed. We follow Abowd et al. (1999) to recode the degree. The degree categories used are reported in Table A.5 with their shares in the panel population.

Table A.5: 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

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 use the information reported in the following ones.[26] Individuals with missing information are excluded from the analysis.

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

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

[26]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.

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.

Appendix B. Adjusted Gini coefficient

Let Y be a positive random variable, 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 $Y|x$. If $L_Y(.|x)$ denotes the Lorenz curve, the Gini coefficient is equal to:

$$G(Y|x) = 1 - 2\int_0^1 L_Y(\theta|x)d\theta \tag{B.1}$$

The Lorenz curve can be written using the quantile function under the regression quantile model as

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

where $\mu_x = E(Y|x)$. See Koenker (2005). Replacing this expression in equation (B.1), entails, after an integration by parts:

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

In the applications in the paper, we estimate the Gini coefficient by using trapezoidal integral approximation with intervals of size $1/K$ and quantile estimates at orders $\theta_1, \ldots, \theta_{K-1}$, with $K = 1$. The approximate formula used is

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

More empirical results on the accuracy of the method are available in the technical report Charnoz et al. (2011).

Appendix C. Additionnal results

Table C.6: 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 C.7: 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 C.8: 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 $H_0 1$ (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 (1982a). 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 C.9: 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 C.10: 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 C.11: 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 C.12: 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 C.13: 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 C.14: 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 C.15: 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_01 (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 C.16: 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

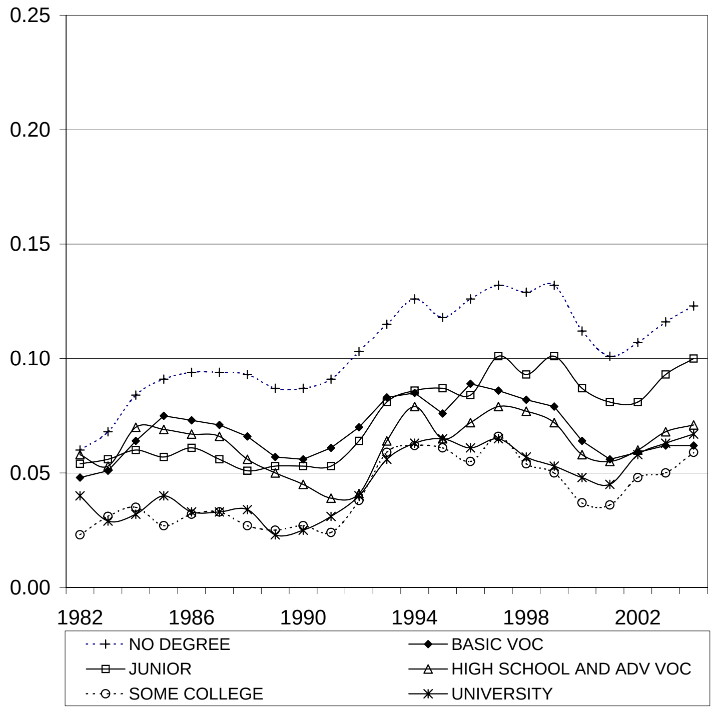
***: p-value$<$ .01, **: p-value$<$ .05, *: p-value$<$ .1.

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

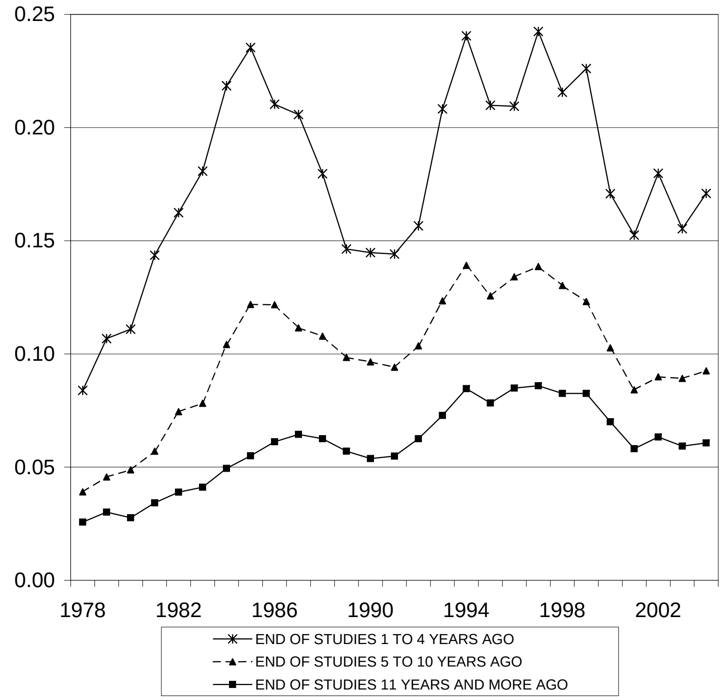
(2) To construct Koenker and Xiao (2002) tests for H_{01} and H_{02}, quantile regressions were performed at orders .1 to .9 by .05 increase. The critical values used are those reported in Table B.1. and B.2. p 318 in Koenker (2005) or were computed thanks to Koenker and Xiao (2002) programs, which were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

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

Appendix D. Additional graphics

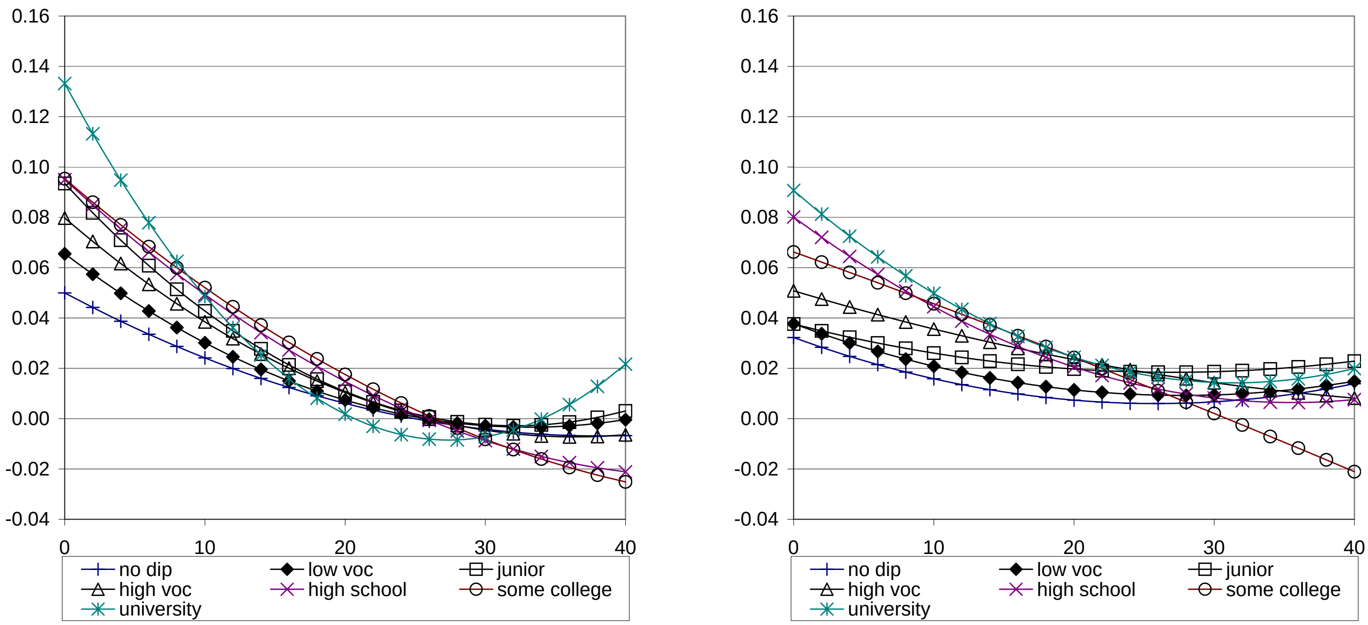


(a) male unemployment rate by education groups (INSEE)



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

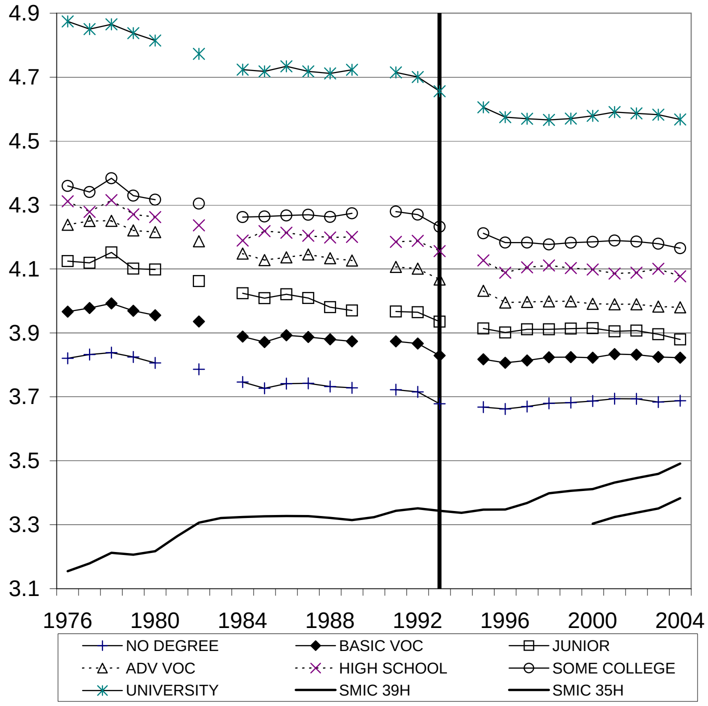
Figure D.10: Male unemployment rates by education groups and potential experience



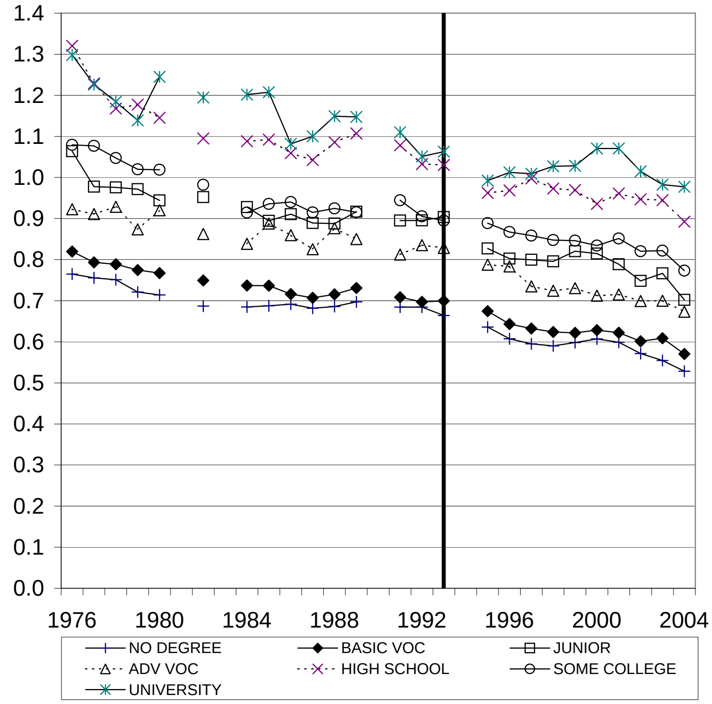
(a) 1976

(b) 2004

Figure D.11: Model (4): LAD estimates of marginal effects of experience.



(a) LAD adjusted log wages



(b) Q90-Q10 log wages differences

Figure D.12: Specification with age: adjusted log wages and Q90-Q10 log wage differences at 30 years old