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ABSTRACT

The Distribution of Earnings in Spain during the 1980s: The Effects of Skill, Unemployment, and Union Power*

In this Paper we analyse changes in the conditional distributions of male earnings in Spain during the 1980s. We use a large new database of records on individual workers and firms from the Spanish social security system for the period 1980–87. The data set is an unbalanced panel subject to censoring due to top and bottom coding. We analyse the behaviour of returns to skill and experience, across sectors and over time. We also study how these returns have been affected over the period by a host of aggregate and sector-specific factors, including unemployment rates and the sectoral coverage of trade union collective agreements.

JEL Classification: J31, J51
Keywords: earnings distributions, returns to skill and experience, unions

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NON-TECHNICAL SUMMARY

Since the early 1980s there has been an increase in wage inequality in the US and the UK. In contrast, wage inequality in France or Germany has experienced very little change. Little is known on the evolution of the wage distribution in Spain due to the lack of suitable microdata. Our contribution in this Paper is to provide the first detailed account of the evolution of wage dispersion in Spain during the 1980s. We do so by using a newly available database of social security records from 1980 to 1987.

We cover two objectives in this Paper. First, we describe the returns to skill and experience by sector and firm size over time. This exercise is complicated by the presence of a substantial amount of top and bottom coding in our data. Second, we use a stylized model of wage-setting in unionized firms as a framework to study empirically the sectoral and aggregate economic variables that determine the returns to skill and experience estimated in the first part.

A first look to the data reveals that over the 1980s there has been an increase in median earnings for the most educated and the most experienced workers but not for other groups of workers. Furthermore, when compared with the evolution of the wage distribution for other countries we find that Spain has followed a mixed pattern. There has been little change in dispersion in the lower part of the distribution, in line with the developments in continental Europe where little change in the wage distribution has occurred, either at the top or at the bottom. On the other hand, we find significant increases in dispersion in the upper part of the distribution, more like the US or the UK – countries that have witnessed increases on both sides of the distribution.

From our more disaggregated first stage estimates we find that indeed the returns to experience and skill have increased over the sample period, with the exception of returns to skill in small firms. We attribute this finding to possible heterogeneity of workers with college degrees in small firms. We also confirm that larger firms tend to pay higher wages, as found in previous studies for other countries. Moreover, we find that earnings had a pro-cyclical evolution over the period.

To understand the economic factors behind the evolution of the different returns estimated in the first part of the Paper, in the second part we first develop a theoretical model with union wage bargaining where unions employ skilled and unskilled labour in imperfectly competitive product markets. One distinctive feature of our model compared to the literature is that unions set wages for unskilled workers only. We formulate it so because we believe this to be better suited to the features of the Spanish labour market. According to the model, wages and returns to skill depend on union bargaining power and reservation utility levels, technological change, the extent of product market competition, and the wage elasticity of skilled labour supply.

We then estimate the effects of empirical measures of the variables suggested by the model on the industry- and year-specific estimates for earnings intercepts, returns to skill, and returns to experience. Due to the limited variability across sectors and time, economic variables turn out not to have large explanatory power over and above sectoral dummy variables. Nevertheless, our results suggest that the following underlying forces affect earnings inequality. Union activity reduces inequality across skill groups, while firm-level bargaining tends to raise it. Long-term unemployment is found to have an asymmetric effect, reducing unskilled workers' earnings but increasing returns to skill, thereby raising inequality. The expected trade-off between earnings of workers of different skill classes and their unemployment rates is evident in the data. Finally, we find that the observed increase in dispersion within the group of college educated workers depends positively on the share of collective bargaining being carried out at the firm level, on the share of educated workers in the population, and on the state of the business cycle. In conclusion, we find that the evolution of the wage distribution in Spain over the 1980s is related to labour supply forces but also to the features of wage bargaining, once cyclical factors are controlled for.

1 Introduction

Since the early 1980s, the UK and the US have witnessed significant increases in wage inequality. In contrast, there has been little change in other countries like France or Germany. Increases in Anglo-Saxon countries have been traced back to rising returns to education and experience, but also to higher differences in remunerations for workers with comparable schooling and seniority. Forces often mentioned as underlying these developments are changes in demographics, changes in labor quality, skill-biased technological change, rising returns to unobserved ability, growing international trade flows, and changes in institutions like declines in minimum wages in real terms or deunionization.

In this paper we provide the first detailed account of the evolution of wages in Spain during the 1980s, distinguishing between changes in inequality arising from changes in the returns to skill and experience and changes in dispersion within observable categories of workers.

We analyze changes in the conditional distributions of male earnings in Spain during the 1980s, using a new database of Social Security records. We employ a sample of monthly earnings for more than 30,000 male employees for the period 1980-1987. It is a matched employer-employee data set, although with a limited number of characteristics recorded for each agent. The data set has the structure of an unbalanced panel subject to censoring due to top and bottom coding in the Social Security records. We first describe the behavior of various quantiles summarizing the evolution of the distribution of real earnings. We then focus on the evolution of the returns to skill and experience, across sectors and over time, taking into account firm size. In a second stage, we attempt to account for the variation of these estimated returns by regressing them on a set of sectoral and national economic variables. The sectoral ones are the coverage of trade union collective agreements, the share of public employment, the hiring rate, and R&D expenditures, whereas the national variables are the share of long-term unemployment, unemployment rates by skill, and changes in the composition of the labor force.

The paper is organized as follows. In section 2 we briefly review some developments in the Spanish economy and its wage bargaining system, and introduce our database. In section 3 we describe the econometric techniques used to analyze the data. In section 4 we show our estimated returns to skill and experience by sector and period, for different firm size classes. We then turn to an empirical assessment of the economic forces behind the evolution of those returns. This is based on a stylized model of wage setting in unionized firms operating in imperfectly competitive markets, presented in section 5. The estimation results from a specification inspired by the model are shown in section 6. Section 7 contains our conclusions.

2 Institutional setting and data description

2.1 Background

Very little is known about the wage distribution in Spain, due to lack of microeconomic data.[1] Sectoral data from the main wage survey, the *Encuesta de Salarios* (which suffers from important shortcomings, for example in terms of coverage), suggest that there was a significant reduction in earnings dispersion across both occupations and sectors in the second half of the 1970s and a slow increase in the 1980s. The standard deviation in hourly earnings (including overtime and bonuses) across occupational categories fell from 0.587 in 1966 to 0.45 in 1977, and then slightly increased to 0.49 in 1987 (García Perea, 1991).[2,3]

The apparent fall in wage dispersion in the 1970s was probably the result of the explosion of pent-up demands for more equality at the time of the establishment of a democratic regime in 1975 coupled with increasing unemployment affecting especially low-wage workers. In the 1980s, several developments potentially affecting wages can be pointed out. The educational level of the labor force rose and the average age of workers fell. The secular decrease in the share of agriculture in the economy was accompanied by a process of restructuring in manufacturing, in the aftermath of the oil shocks of the 1970s, which caused much employment turbulence. Restructuring allowed for technological catch-up in the midst of a long recession which only ended in the second half of 1985. The prospect of European Community membership favored a steady increase in the degree of openness of the economy, which was strengthened after 1985. Wage bargaining institutions were definitely enshrined in the law in 1980, with the approval of the so-called Workers' Statute. In contrast with the decline of unionization experienced in Anglo-Saxon countries, over the first half of the 1980s union power was being established in Spain. Lastly, during this period, the unemployment rate increased dramatically, from around 11% in 1980 to above 21% in 1985, then falling only slightly to around 20% in 1987. The increase in unemployment hit low-skill workers more than high-skill ones (see below).

[1] Recently, some studies on returns to education have been carried out with earnings data from decadal and quarterly Family Expenditure Surveys, for a review see Oliver *et al.* (1999).

[2] Similar data appear in Jimeno and Toharia (1994). Melis and Díaz (1993) report an increase in nominal annual labor earnings inequality from 1986 to 1990, based on data on single-earner Spanish income tax returns.

[3] Abadíe (1997) carried out a conditional quantile analysis of earnings using cross-sections from the Family Expenditure Surveys for 1980 and 1990. He found that returns to education fell at most quantiles, except for the younger college-educated cohorts.

2.2 The Spanish wage setting system

In Spain, wages are essentially set by collective bargaining. Slightly less than 15% of all employees are covered by firm-level agreements, while almost 70% are covered by agreements with a broader scope. Most agreements are bargained for at a quite centralized level, usually applying to an economic sector, although for bargaining purposes sectors do not correspond to the usual standard sectoral classifications, and they may be broad or narrowly defined. Sectoral agreements usually apply to a whole province, which are sub-units of regions, although they can also cover one region, several regions, or even the whole country. The agreements determine the wage scale for different occupations.

There are two main unions, organized along economic sector and regional lines, and a few smaller unions typically with regional scope. Employer organizations are structured along the same lines as the major unions, within a single confederation of organizations. In order to be entitled to participate in collective bargains, a union needs to obtain at least 15% of the votes in the elections for worker representatives (held every 4 years) in the sector of reference, or 10% of the votes at the national level. Union density is very low, around 10 to 15%. However, this is not very relevant, because the advantages of being a union member are scant: conditions agreed in collective agreements are legally binding, as minima, for all workers in the appropriate economic and geographical domain and occupation, regardless of union affiliation. Thus, affiliation is quite irrelevant in Spain and a better proxy for union power is the coverage of collective bargains as a percentage of the total number of employees in a sector, although it is not a high-quality measure. In the sample period spanned by our data, the aggregate number of collective agreements and their coverage increased steadily.

Sectoral union coverage ratios vary widely at the beginning of the sample period: it is low in Construction and Other services and high in Mining and Manufacturing (see Table A3).[4] What explains this sectoral variability? As described above, coverage will be higher the wider the definition of the sectors for collective bargaining purposes (with some sub-sectors ending up not covered) and the wider the geographical area of applicability. It will also depend on the presence of public employment in the sector, because coverage is usually higher for public (non-tenured) employees and employees in public firms than for private employees. Lastly, coverage tends to be lower in services than in other sectors (as is common in many other countries). Collective bargaining was already established in the Franco regime, in 1958, through a type of laws called the *Ordenanzas laborales*. Somewhat surprisingly, the sectoral structure set during the dictatorship period did not vary much with the advent of democracy in 1977.[5] As to

[4]It is also high in Finance, though there are problems with data on this sector at the beginning of the sample. Also, some sectors show coverage above 100%, which stems from having different sources for the numerator and the denominator of the coverage ratio. This is discussed in Appendix 1.

[5]For descriptions see Escobar (1995) or Abellán *et al.* (1997).

the time-series evolution of sectoral coverage ratios in our sample period, it can be interpreted as a quite mechanical drive by unions to increase coverage in all sectors. Over the 1980's, then, coverage tends to converge to very high proportions: by 1987 all sectors, except Other services, end up between 83% and full coverage, with the average around 95% (see Table A3).[6]

Collective bargains are much more relevant for low-skill than for high-skill workers. For instance, Dolado *et al.* (1997) find, from a 1990-91 survey, that no high-skill worker reported an average hourly wage which was below the minimum wage guaranteed in collective bargains for their corresponding sector and skill/professional status (including seniority and overtime premia), while 41% of the unskilled did. Similarly, the average waged reported by high-skill workers was 57% higher than such minimum guaranteed wage, while it was only 0.2% higher for low-skill workers. Thus, while wages may be formally bargained for all workers, bargained wages are seldom applicable to high-skill ones.

Sectoral collective bargains usually determine wages and annual hours of work only. Three quarters of workers covered are under one-year agreements, while agreements for two years usually contemplate their conditions to be revised at the end of the first year. For all but the last two years covered by our database, 1980-87, there were also nationwide collective agreements setting wage growth rate bands (of 2 to 4 percentage points width, depending on the year) applicable to all Spanish workers.[7]

In the period covered by our data, there were three national legal minimum wage levels, for workers up to 16 years old, for 17 year olds, and for older workers. The relative values of the first and second to the third were around 39% and 61%, respectively.[8] Minimum wages were raised annually by the inflation rate expected at the end of the previous year.

2.3 Characteristics of the database

We use a database of Spanish Social Security records. It contains the information provided monthly by firms when paying contributions for their employees. This information was matched, by the Spanish Ministry of Labor, with workers' and firms' individual records at the Social Security system. The matched database contains information on workers' characteristics, i.e. sex, age, occupation, and pre-tax monthly earnings, and on the firm they work for, i.e. its sector, region of location, and size

[6] As a result, we would not expect union coverage to depend much on observed wage growth or wage differentials, as might have been the case with union affiliation (if this was a relevant variable in the Spanish case).

[7] The actual bands were: 11-15% (1981), 9-11% (1982), 9.5-2.5% (1983), 5.5-7.5% (1985), and 7.2-8.6% (1986). There were no agreements in 1984 and 1987. Further description can be found in Jimeno (1992) and Jimeno and Toharia (1994).

[8] Their respective monthly values in 1985 were: 14,370; 22,800; and 37,170 pesetas.

(number of workers).

The type of data source determines some special characteristics of the earnings variable available. In particular, we observe the taxable earnings base, rather than actual earnings, which is subject to floors and ceilings which depend on the worker's occupation and vary over time. This causes the censoring of earnings for a fraction of the observations, most of them at the top. Moreover, this earnings variable excludes overtime payments, travel allowances, occasional payments, and fringe benefits.

There is another data problem. In Spain all employees are entitled to receive statutory bonuses, equal to one extra installment of the regular monthly pay, in July and December.[9] In some sectors and firms, workers get additional bonuses. By law, in their declaration of taxable earnings for Social Security purposes, firms must evenly spread bonus pay amounts over the year. However, before January 1983 spreading was compulsory for the July and December bonuses only, not for any additional ones. As a consequence, reported earnings in our sample may be artificially low before 1983, for workers with 3 or more bonus payments per year.

The criteria followed to construct the final database are as follows.[10]

(*a*) *Definition of earnings.* The database does not contain information on either days of work per month or hours of work per day, which precludes the computation of hourly wages. As a result, we analyze the behavior of monthly earnings.

(b) Sex and age. There is no information on workers' marital status or other family characteristics, like the number of children. We deem these to be especially important for the labor supply of married women, so we analyze male earnings only. We also exclude from the sample workers aged 16 to 19, due to the instability of their attachment to the labor market, and men aged 65 or older, due to the importance of transitions to retirement at those ages. This leaves us with men aged 20 to 64.

(c) Working time. As a way to target full-time, full-month employees, we exclude workers with reported monthly earnings below the floor for the taxable earnings base in their occupation.

(d) Sector. The data set covers private sector, non-tenured public sector, and State-owned enterprise employees. We analyze data on workers in the non-agricultural sector only, because the coverage of the sample for the agricultural sector in the database is quite limited. At the empirical estimation stage we distinguish between 8 sectors, roughly corresponding to the usual one-digit classification.

(e) Period and frequency. The data refer to the months of June and December, starting in December 1980 and ending in December 1987. We discard the June data, to suppress the effects of seasonality, and retain only those referring to December. In this section we provide descriptive statistics for 1980-87. Later on, in the econometric

[9] If the corresponding collective bargain allows it, workers can choose to spread receipt of these statutory bonuses evenly over the year.

[10] See Appendix 1 for details.

analysis, we drop the first year due to lack of availability of one sectoral variable used as a regressor.

The original database contains close to 6 million observations, on about 600,000 workers. After applying a set of filters described in Appendix 1, we drew a random sample comprising 30% of the remaining total, and were left with 140,545 observations from the filtered database, which refer to 32,291 workers.

The most relevant characteristics of the observations in such sample are contained in Table A1. Almost all of the 19% censored observations are top-coded. The number of observations per individual varies, with 34% of them being observed for the full 7 years spanned by the sample.

A key variable is the skill level. As a measure of skill we use a grouping by education of occupational categories. The number of years of schooling is not observed, but the database provides information on occupation. There are 10 occupational groups, but most do not correspond to educational levels. Thus we focus on three occupations which correspond to educational groups: workers with a *college* degree (*licenciados*, with at least 5 years of higher education), workers with a *junior college* degree (*diplomados*, with at least 3 years of higher education), and individuals working in *unskilled* jobs (*peones*). The remaining group, including all workers in between the last two groups, is labeled as *medium-skilled.*

Another variable we use later on is firm size. We distinguish between 3 classes: *small* firms, with up to 100 employees, *medium-sized* firms, between 101 and 1,000 employees, and *large* firms, above 1,000 employees. We do not, however, use the information on regions in the database, for reasons to be explained below.

2.4 A first look at earnings in Spain in the 1980s

The period 1980-1987 was a relatively slow growth period, with an average annual GDP growth rate of 2.3%. But this comprises part of a recession, 1980-85, with a 1.5% growth rate, and part of a boom, 1986-87, with a 4.4% growth rate. Over the whole period, wages bargained in collective agreements fell in real terms by 1% per year while, owing to wage drift, real wages managed simply to stagnate, with a yearly growth rate of –0.02% per year.

Our sample shows similar behavior, with median monthly earnings for all workers, deflated by the national consumer price index (CPI), decreasing by 0.19% per year.[11] As shown in Table 1, the evolution is quite different for workers with college education, whose median earnings increased by 1.37% per year, than for unskilled workers, whose earnings fell by 0.37%. Figure 1 shows these variables, normalized in 1980.[12] Patterns

[11] Note that these facts refer to a sample whose demographic composition changes every year.

[12] The evolution of medians and dispersion measures is very similar for the 1983-87 period, which is free of potential measurement error arising from the change in the regulation on reporting of bonuses discussed in the previous subsection.

also differ by age: young workers' earnings fell by 1.73% per year, while for the oldest group there was an increase of 1.35%; Figure 2 shows the evolution of medians by age group for unskilled workers.[13]

These differences suggest an increase in the returns to skill and experience. Table 2 helps make this general impression more precise. It shows a bigger increase in the earnings of college educated workers vis-a-vis unskilled ones for middle-aged workers than for younger ones, while top censoring precludes observation for older workers. It also shows a pronounced increase in the returns to experience for unskilled workers, while information for college educated workers is again top censored. Table 1 highlights quite diverging earnings trends across sectors as well, with a range going from -0.84% in Construction to 1.07% in Mining (it is probably higher in Finance, but the median is top censored).

Due to censoring in our data, we cannot provide the usual measures of earnings dispersion (e.g. the Gini coefficient or the variance of log earnings). We can nevertheless show quantiles based on relative earnings categories. The most widely quoted measure, the (log) difference between the 90th and the 10th percentile, $P90$-10, is unfortunately also censored in our data. Table 1 shows two measures for log earnings: the difference between the 75th and the 25th percentile, $P75$-25, or interquartile range, which captures dispersion around the median, and the 50-25 percentile difference, $P50$-25, which measures dispersion in the lower half of the earnings distribution.

Earnings dispersion clearly increases when all workers are considered. Figure 3 shows kernel density estimates of the earnings distributions in the initial and final years. In comparison with 1980, in 1987 a significant amount of frequency mass moves away from the middle of the distribution, mostly to the upper half. In addition, Table 1 shows that inequality rises both around the median, by 7.5 percentage points according to the $P75$-25 measure, and below the median, by 0.9 percentage points according to the $P50$-25 measure.

We cannot fully characterize dispersion within skill cells, due to top-coding for higher skill groups. Nevertheless, Figure 4 shows a clear shift to the right in the distribution of earnings for college educated workers. For the bottom half of the distribution, Table 1 also indicates increased inequality among college educated workers, but a fall among workers with a junior college degree. Inequality also rises, slightly, among the unskilled. For this group, Figure 5 shows lower mass at higher earnings (though not at the very top) of the 1987 distribution as compared with 1980, which is reflected in the increasing dispersion shown in Table 1 (see also Figure 6). Moreover, the difference between the 90th and 10th percentiles, which is not censored for this skill group, rises

[13] Note also that due to variation in top codes, there may be censored earnings observations below the median, even if the median itself is not censored. The effect of this would be to downward bias the median. This is not an issue for the college, junior college, and unskilled categories, but may be so for the catch-all medium-skill one, and for aggregate earnings measures that do not control for skill category.

from 0.652 to 0.674 over the period.

Regarding age, inequality drops among young workers but grows for older workers, especially among the middle-aged. Within sectors, inequality increases everywhere except in Construction and Transportation and public utilities, which suggests that a simple explanation of rising inequality based on a shift of employment shares towards sectors with higher dispersion cannot be the whole story.

How does the Spanish experience compare internationally? Some illustrative data are provided in Table 3 for male wages during our period of reference, 1980-87, in several countries. A rigorous comparison is difficult to carry out. First, different measures of wages are available for each country (hourly, monthly, etc.), and for this reason comparisons of levels are not fully appropriate. Secondly, for most countries only the $P90/50$ ratio, for dispersion above the median, and $P50/10$ ratio, for dispersion below the median are usually quoted, whereas in our data for Spain those ratios are censored. Thus, for all countries we present those two ratios, while for Spain and the US we also show the $P75/50$ and the $P50/25$ ratios.

Continental European countries show a pattern of a relatively small increase in dispersion above the median and a reduction in dispersion below the median. On the other hand, Anglo-Saxon countries show increased dispersion both ways. Spain follows a European pattern in that there is little change in dispersion in the lower part of the wage distribution.[14] On the other hand, Spain experienced a very significant increase in dispersion on the upper part, which is actually higher than that observed in the US over the same period.

We can set these observations against the evolution of the population of working age over the period. Table 4 presents some data for Spain, where we use the total population aged 16-64 as the reference. The table shows that there was an increase in the share of workers between 20 and 44 years old in the population, mostly at the expense of the eldest cohort (45-64 years old). There was also a uniform shift towards higher schooling which however, as shown in Table 3, is lower than in the most developed OECD countries. Thus, the reduced relative supply of older workers is consistent with the rising returns to experience, at least for the eldest group of workers, while the rising supply of educated workers suggests that increases in the demand for skilled workers must have also been at work in bringing about the observed rise in the returns to skill.

As to sectors, Table 4 reveals a very significant employment shift into services from all remaining sectors, especially from agriculture. As indicated by Table 3, this shift is relatively large by international standards. To the extent that employment in some services has a higher skill content than employment in other sectors, this may be a further factor helping account for the increase in the returns to skill. There may be,

[14]This is probably related to the operation of both the legal minimum wage and, especially, the relatively high minimum wages prevalent in sectoral collective agreements (see Bover *et al.*, 1999).

of course, increases in the demands for skill within sectors. Table 4 also reveals that from 1980 to 1987 the unemployment rate increased by about 6 percentage points for the college and junior college graduates, and by around 9.5 points for the lower skill categories. As is well known, the rise in unemployment in Spain is higher than in most other countries, and its evolution may have affected the wage distribution. In particular, it may have had an apparent wage compression effect through a change in the composition of employment, if workers with the least ability represent a disproportionate share of the pool of unskilled unemployed workers, since these workers' wages disappear from the observed wage distribution when they become unemployed.

The statistics above are suggestive but only have a limited descriptive value. In section 4 we provide a more disaggregate analysis, by computing returns to skill and experience broken down by firm size, sector, and year employing a statistical model. At that stage we use a likelihood estimation procedure, described in section 3, to overcome the problem of censoring. At a second stage, we also try more rigorously to elicit economic forces underlying the structure and evolution of estimated returns to skill and experience, presented in section 6, as suggested by an economic model described in section 5.

3 Econometric techniques

Our data set is an unbalanced panel subject to both left and right censoring, due to bottom and top coding in the Social Security records. Top coding, however, introduces a more severe form of censoring in our empirical conditional earnings distributions than bottom coding.

Letting w_{it}^* denote the underlying log earnings and w_{it} the observed censored log earnings variable, we have

$$w_{it} = d_{1it}c_{1t} + d_{2it}c_{2t} + (1 - d_{1it} - d_{2it})w_{it}^*$$

where c_{1t} and c_{2t} represent the (log) top and bottom codes, respectively, and d_{1it} and d_{2it} are the censoring indicators:

$$d_{1it} = \mathbf{1}(w_{it}^* \leq c_{1t}),\ d_{2it} = \mathbf{1}(w_{it}^* \geq c_{2t}).$$

We conduct our empirical investigation in two stages. In the first one, we are interested in analyzing, over time and across industries, the conditional distributions of log earnings given a set of individual and firm characteristics x_{it} (education –four groups–, age –by year–, and firm size –three groups–). In our data, the censoring points depend on x, but we omit the dependence to simplify the presentation.

Obviously, only the non-censored portions of the conditional distributions of log-earnings are non-parametrically identified, with the severity of censoring varying according to x_{it}. Specifically, the θ-th quantile of w_{it}^* given $x_{it} = \xi$, $Quant_\theta(w_{it}^* \mid x_{it} = \xi)$, is non-parametrically identified from the censored data provided

$$\theta_1^*(\xi) < \theta < \theta_2^*(\xi),$$

where

$$\begin{aligned}\theta_1^*(\xi) &= \Pr(w_{it} \leq c_{1t} \mid x_{it} = \xi) \\ \theta_2^*(\xi) &= \Pr(w_{it} \leq c_{2t} \mid x_{it} = \xi)\end{aligned}$$

or alternatively, we can write:

$$Quant_\theta(w_{it} \mid x_{it}) = \begin{cases} c_{1t} & if \quad Quant_\theta(w_{it}^* \mid x_{it}) \leq c_{1t} \\ Quant_\theta(w_{it}^* \mid x_{it}) & if \quad c_{1t} < Quant_\theta(w_{it}^* \mid x_{it}) < c_{2t} \\ c_{2t} & if \quad Quant_\theta(w_{it}^* \mid x_{it}) \geq c_{2t}. \end{cases}$$

Here we wish to focus on the modelling of single summary measures of position and dispersion of the conditional distributions of earnings. We proceed by adjusting a normal model with a heteroskedastic variance to the censored data. As an alternative, we could model the conditional median and the conditional interquartile range on the basis of the non-censored observations. Such procedure, however, while apparently more robust, would crucially rely on functional form assumptions when drawing conclusions about the entire median and interquartile regression functions. Log-normality, of course, imposes a strong, not fully testable, parametric assumption on the data, but relative to it, we can make an efficient use of the information to conduct specification searches about the conditional mean and variance of log earnings.

Assuming that log earnings in year t at industry s are conditionally normal,

$$w_{its}^* \mid x_{it} \sim N[\mu_{ts}(x_{it}), \sigma_{ts}^2(x_{it})],$$

an individual observation's contribution to the log-likelihood function for the censored panel takes the form:

$$\begin{aligned} L_{its} &= d_{1it} \log \Phi\left(\frac{w_{its} - \mu_{its}}{\sigma_{its}}\right) + d_{2it} \log\left[1 - \Phi\left(\frac{w_{its} - \mu_{its}}{\sigma_{its}}\right)\right] \\ &\quad -\frac{1}{2}(1 - d_{1it} - d_{2it})\left[\log \sigma_{it}^2 + \frac{(w_{its} - \mu_{its})^2}{\sigma_{its}^2}\right]. \end{aligned}$$

In this expression, the first term represents the contribution to the likelihood if it is a bottom coded observation, the second term if it is top coded, and the last term if it is not censored.

In the empirical analysis, we use linear and exponential representations for μ_{its} and σ_{its}^2, respectively, allowing for firm-size specific returns to education, and linear and quadratic age effects:

$$\begin{aligned} \mu_{its} &\equiv \mu_{ts}(x_{it}) = z_{it}'\beta_{ts} \\ \sigma_{its}^2 &\equiv \sigma_{ts}^2(x_{it}) = \exp(z_{it}'\gamma_{ts}). \end{aligned}$$

The vector of variables z_{it} can be described as:

$$\begin{aligned} z'_{it} &= (s1, s2, s3, ed1 \times s1, ed2 \times s1, ed3 \times s1, \\ &\quad ed1 \times (s2+s3), ed2 \times (s2+s3), ed3 \times (s2+s3), age, age^2)_{it} \end{aligned}$$

where sj and edj $(j = 1, 2, 3)$ denote, respectively, firm-size and education category dummy variables.

In the second stage, we investigate the relationship of the coefficients β_{ts} and γ_{ts} with aggregate and industry specific economic variables. From the point of view of estimation this can be regarded as imposing restrictions on the previous coefficients using minimum distance techniques.

Let the specification for the jth coefficient β_{jts} be of the form

$$\beta_{jts} = h'_{ts}\delta_j \qquad (t = 1, ..., T;\ s = 1, ..., S)$$

where h_{ts} is a vector of aggregate and industry variables including a constant term (the presentation for the coefficients γ_{jts} in the conditional variance would be similar to this). In stacked form, we can write $\beta_j = H\delta_j$, where β_j is a TS vector containing the β_{jts} and H is a TS-rowed matrix whose rows are given by h'_{ts}. A minimum distance estimate of δ_j is

$$\widehat{\delta}_j = (H'AH)^{-1}H'A\widehat{\beta}_j$$

where $\widehat{\beta}_j$ is the vector of the unrestricted estimates $\widehat{\beta}_{jts}$, and A is a weighting matrix. Under the assumption of correct specification, the optimal choice of A is a consistent estimate of the inverse of the asymptotic variance of $\widehat{\beta}_j$, but plim $\widehat{\delta}_j$ is invariant to the choice of A. However, under misspecification the probability limit of $\widehat{\delta}_j$ will depend on A.[15] Since in our setting we do not expect the h_{ts} variables to account for all the variation in the β_{jts}, "misspecification" is to be expected. Thus, it seems appropriate to choose A in such a way that plim $(\widehat{\delta}_j)$ represents an easily interpretable summary statistic. We considered two such choices for A leading to OLS ($A = I$) and weighted least squares by industry size (A equal to a diagonal matrix of industry weights). In both cases consistent standard errors robust to misspecification were obtained from:

$$\widehat{Var}(\widehat{\delta}_j) = (H'AH)^{-1}H'A\widehat{Var}(\widehat{\beta}_j)AH(H'AH)^{-1}.$$

Note that our method in two stages could be reduced to one by considering a pooled log-likelihood function for all periods and industries, subject to the restrictions implied by the dependence of returns on sectoral variables:

$$L(\delta) = \sum_t \sum_s L_{ts}(\mu_{ts}, \sigma^2_{ts}).$$

[15]In general, for a fixed A: plim $\widehat{\delta}_j = (H'AH)^{-1}H'A\beta_j$. If $\beta_j = H\delta_j$ then plim $\widehat{\delta}_j = \delta_j$ for any A. But if $\beta_j \neq H\delta_j$, $(H'AH)^{-1}H'A\beta_j$ is a pseudo true parameter whose value depends on A.

We did not pursue such method because of a computational disadvantage (i.e. having to maximize over the full data set), but more fundamentally because it would require to impose all the restrictions simultaneously. As a result the estimated effects would be more sensitive to misspecification. Moreover, we are interested in analyzing first stage results *per se*, independently of our ability to relate them to economic variables in the second stage.

The assumption of conditional independence across workers is more plausible than that of independence over time of the observations for a given worker. In the event of autocorrelation, $L(\delta)$ will only be a pseudo log-likelihood, but our period-specific log-likelihoods will remain unaltered. Nevertheless, the estimated $\widehat{\beta}_{jts}$ for different periods will be correlated, what will potentially affect the consistency of the estimates of $Var(\widehat{\beta}_j)$ that we employ.

4 The evolution of earnings and returns to skill and experience

We now describe the results from our estimation of an earnings equation for each industry and year. Our aim is to obtain estimates of the returns to skill and experience. As described in section 3, in a second stage these estimates are themselves regressed on a set of sectoral and aggregate economic variables.

Although the database included information on the firm's region of location, we do not use it. The reason is that there are hardly any data available on economic variables varying simultaneously by region and sector and thus, having to choose, we considered the sectoral variation more important from an economic point of view than regional variation.

We introduce as regressors observable characteristics of workers and firms. Returns to potential experience are meant to be captured by the worker's *Age*, measured in years, and its square. All remaining regressors are dummy variables. Returns to skill are captured by the skill variable discussed in section 2, which considers four groups: *College* graduates, *Junior college* graduates, *Medium-skilled* workers, and *Unskilled* workers. Employer-size is captured through a breakdown into three categories: *Small, Medium-sized,* and *Large* firms.

We estimate the following specification for conditional mean log earnings for each industry ($s = 1, ..., 8$) and year ($t = 1981, ..., 1987$):[16]

[16] We lose the first year in the sample, 1980, due to the unavailability of one sectoral variable used at the second stage below –union coverage–.

$$
\begin{aligned}
\mu_{its} \;=\;& \beta_{1ts}\, Small \;+\; \beta_{2ts}\, Medium\text{-}sized \;+\; \beta_{3ts}\, Large \\
&+ \beta_{4ts}\, College \times Small \\
&+ \beta_{5ts}\, College \times (Medium\text{-}sized + Large) \\
&+ \beta_{6ts}\, Junior\ college \times Small \\
&+ \beta_{7st}\, Junior\ college \times (Medium\text{-}sized + Large) \\
&+ \beta_{8ts}\, Medium\ skilled \times Small \\
&+ \beta_{9ts}\, Medium\ skilled \times (Medium\text{-}sized + Large) \\
&+ \beta_{10ts}\, Age \;+\; \beta_{11ts}\, Age^2 \qquad (1)
\end{aligned}
$$

and a similar specification for the log of the conditional variance of log earnings.

Estimates of returns to skill from sectoral regressions may be biased if there is dynamic self-selection of workers to those sectors where their returns are higher. However in our case we can essentially treat sectoral adscription as a fixed effect since in our sample a very small proportion of workers change sector from one year to the next (below 1%).

Unskilled workers constitute the reference (i.e. omitted) group, so that the β coefficients capture returns vis-a-vis that group. Equation (1) shows that returns to skill are allowed to vary between small firms and larger ones only, large and medium-sized firms having been pooled in these interactions so as to save on degrees of freedom. Average returns to a given characteristic are obtained by averaging the estimated β_{jts} coefficients across sectors, using the number of observations as weights. For instance, average returns to college in small firms in 1981 are given by:

$$\overline{\beta}_{1981}^{c,small} = \frac{1}{N_{1981}^{c,small}} \sum_s \widehat{\beta}_{4,1981,s} N_{1981,s}^{c,small}$$

where $N_s^{c,small}$ denotes the number of observations belonging to workers with a college education working at small firms in sector s.

4.1 Estimated earnings and returns to skill and experience

The first stage provides us with estimates for four blocks of variables: (a) the common component of earnings for all workers or *basic earnings*, separately for small, medium-sized, and large firms ($\widehat{\beta}_{1ts}$ to $\widehat{\beta}_{3ts}$); (b) *returns to college*, separately for small and medium-large firms ($\widehat{\beta}_{4ts}$ and $\widehat{\beta}_{5ts}$); (c) *returns to junior college*, also for small and medium-large firms ($\widehat{\beta}_{6ts}$ and $\widehat{\beta}_{7ts}$); and (d) *returns to experience (age)* ($\widehat{\beta}_{10ts}$+2$\widehat{\beta}_{11ts}Age$). We also obtain results for the medium-skill group, but we will hardly present them, given that the heterogeneity of education among workers within this group makes it difficult to provide an economic interpretation for them.

We discuss the results of the first stage estimation using graphs. Starting with earnings levels, Figure 7 shows how they are affected by firm size, for different educational categories. The pictures portray the sum of basic earnings plus the interaction of the respective skill dummy with the firm size dummy. For example, the bottom line in panel (a) of Figure 7 corresponds to college-educated workers in small firms, i.e. the weighted average of the sum $\widehat{\beta}_{1ts} + \widehat{\beta}_{4ts}$.

The figure indicates that, in general, larger firms pay their workers more than smaller firms at all educational levels, but particularly at the college level. This accords with the well-known employer size-wage effect described by Brown and Medoff (1989). Several factors may underlie this effect, ranging from neoclassical explanations (larger firms employ higher-quality workers, they have greater capital intensity, or they pay higher wages to reduce monitoring costs –which are presumably more important than in smaller firms– or to compensate for worse working conditions) to more institutional ones (larger firms have more monopoly power or, in the US, they pay higher wages in the non-union sector to avoid unionization). None of these explanations receives strong empirical support, so that no wide consensus has been reached yet on the most important sources of the size-wage effect, as indicated by the survey by Oi and Idson (1999), although these authors' reading of the evidence leads them towards the explanation based on workers being more able in large firms (Idson and Oi, 1999).

Aside from this difference in levels, the evolution is similar across firm sizes: earnings go down until 1985 and then recover in 1986-87 for all groups, except for college degree workers. But the size of the recovery varies. Basic earnings and earnings of medium-skilled workers end up lower in 1987 than in 1981 for all firm sizes. Workers with college or junior college degrees end up about level. The two outliers are workers in large firms with a junior college degree, whose earnings increase, and those in small firms with a college degree, whose earnings fall.

We now focus on the returns to college and junior college. The top panels of Figures 9 to 12 indicate that, as happened for total earnings, returns to college are larger in medium-large firms than in small firms, but returns to junior college are similar in both size classes.

As to their evolution, the top panels of Figures 10 and 12 show significant increases for both returns in medium-large firms. Returns to junior college in small firms are essentially flat, the mild increase apparent in Figure 11 (a) being the effect of an outlying sector (see below). The most striking result is the decrease, for small firms, in the returns to college. We will discuss this finding below, in section 6.1, once we have gathered further empirical results. For now, let us just say that this finding is consistent with the idea, advanced above, that employees in smaller firms are less productive than those in larger firms, and hence they command lower wages in the labor market. Alternatively, it may be an effect of composition. In small firms the proportion of clerical workers with college and junior college degrees is bigger than at large firms and, moreover, that proportion appears to have risen and this pulls down the mean. This composition effect might also explain in part why, in small firms, returns to junior college are about the same as returns to college at the end of the sample (cf. the top panels of Figures 9 and 11), and also the increasing difference between small and medium-large firms in the returns to college. This composition hypothesis receives some support when we estimate and explain the behavior of conditional variances (see below).

It is instructive to look at these estimates at a disaggregated level, shown in Figure 8 for small firms (patterns are similar across size classes). The Basic earnings are highest in Construction (1), where unskilled workers are valued the most, and lowest in Finance, insurance, and real estate (5). As to returns to college, the downward trend in small firms (Figure 9) mainly reflects the falling returns in Transportation and public utilities (3) and Finance (5), which, together with Mining (8), have been the sectors with the highest returns to college within that size class. Indeed, Mining is the only sector with a clear upward trend, a result which would be consistent with a compositional interpretation of the overall downward pattern in small firms (i.e. high-education workers are more homogeneous in this sector). As for medium-large firms, the upward trend in the returns to college is present in all sectors (Figure 10). The mildly increasing average estimate of returns to junior college in small firms (Figure 11) is fully driven by Transportation and public utilities (3); it becomes constant when this sector is left out. In contrast, the upward trend in these returns in medium-large firms (Figure 12) is widespread, and remains when Trade (4) is excluded.

Returns to potential experience, proxied by age, are shown in Figure 13. As expected, these returns are higher the younger the worker; given concavity, the earnings profile peaks around 45-55 years old, depending on sector and firm size. Over the period, returns to experience remain roughly constant for the youngest workers (e.g. 22 years old) and increase for older ones. By sectors, it is in Finance (5) that young workers get the highest returns, although these decrease rapidly over the life-cycle so that this sector ends up having the lowest returns for older workers (cf. panels (b) and (d)). While specially acute in Finance, most sectors show an increase in the returns to experience over the whole period.

In conclusion, the main stylized facts arising from our estimates are as follows: (i) pay is positively related to firm size; (ii) basic earnings fall until 1985 and rise thereafter; (iii) in medium-sized and large firms, returns to both college and junior college rise; (iv) in small firms, returns to junior college remain essentially constant (except for Transportation and Public utilities, with a sharp increase in 1986-87) while returns to college clearly fall, and (v) returns to potential experience steadily increase over the period.

4.2 Estimated conditional variances

Our estimates, graphed in Figure 14, show that behavior of the log conditional variance of log earnings varies with skill type.[17] For college and junior college earnings, the variance is in general lower the larger the firm; while for medium-skilled and basic earnings, it is smaller and similar for all firm sizes, with no stable ranking across size groups. The two high-skill groups experience an increasing variance over time, although for junior college graduates this is marked only in small firms, where it results from the behavior of only one sector (Transportation and public utilities), as discussed below. The lowest two skill groups show little change in variance over time.[18]

Indeed, the conditional variance for college education increases significantly regardless of firm size (Figure 15) and sector.[19] On the other hand, the variance for junior college increases mostly after 1985 (Figure 16). This variance is plotted both including and excluding Transportation and public utilities, in view of the enormous increase in variance experienced in small firms belonging to this sector in 1986-87. Overall, for all but medium-skill earnings, Transportation and public utilities has the highest variance, whereas Mining is a high variance sector in basic earnings, as are Construction and Trade for junior college. Finance shows an increasing variance for college, which reaches high values from 1985 on.

Lastly, the variance is higher the younger the worker is, and shows no trend over the 1980s (Figure 17). By sector, Trade has the highest variance for young workers and the lowest for older ones.

5 A stylized model of wage setting

In the second stage of our empirical analysis we wish to study the determinants of the evolution of basic earnings and returns to skill and experience. In the literature this is typically done by examining changes in the supply of and the demand for labor of different types. Thus, for example, in the US a key issue has been to explain why, in the face of sizable increases in the supply of highly educated labor, the returns to skill have experienced a significant increase in the 1980s and 1990s. The key factors explaining this puzzle appear to have been the increase in physical capital, which is presumed to be complementary with skills, and skill-biased technological progress (see, e.g. Katz and Murphy, 1992, or Mincer, 1991).

[17] This refers to the sum of the variance intercept estimate by size plus the coefficient on the interaction between the skill dummies and the size dummies.

[18] Graphs for conditional variances by sector are not presented to save space, but are available upon request.

[19] This refers to the estimates for skill groups interacted with firm size groups, i.e. not considering the intercepts by size.

In section 2 we saw that some of the labor supply changes experienced in Spain conform, to a higher or lower degree, to those experienced in other OECD countries. Thus, in our empirical analysis we will consider such changes. However, our data set for Spain covers a relatively short period (7 years), spanning less than a full business cycle, rather than the long periods over which labor supply and demand interplay so as to determine equilibrium returns to skill. Our goal is to investigate other types of potentially relevant factors, considering in particular labor market institutions, which show enough variation over the sample.[20] As described in section 2, wages are set in Spain in a relatively centralized way, with labor unions playing a key role. Thus, our next step is to develop a theoretical framework with union wage bargaining at the center, which will serve us a guide for the empirical analysis of the evolution of the estimated returns to skill and experience presented in the preceding section.

There exists some literature on the effects of unions on returns to skill and wage inequality, most of which is empirical, generally finding that unions tend to compress the wage structure.[21] A recent theoretical model is provided in Acemoglu *et al.* (2000), which focuses on skill-biased tecnological change and assumes that unions play two roles: they set wages for both skilled and unskilled workers, thereby compressing wages, and they impede the firing of unskilled employees. The main result in that framework is that the increase in wage inequality is caused by skill-biased technological change rather than by deunionization, but the latter does amplify the effects of the former. In contrast, in our model unions only set wages for unskilled workers and do not play any role in firing decisions. These two features seem to us to be better suited to the features of the Spanish labor market, as described in Section 2.

We now present a simple model of wage bargaining at firms employing two types of labor, skilled and unskilled, and operating in imperfectly competitive product markets.

5.1 Product market structure and labor demand

For unskilled workers, wage setting is assumed to follow the right-to-manage structure, by which wages are set through bargaining between worker representatives and the firm's managers (hereafter called the firm).[22] Then, after the unskilled wage is set, the firm chooses the quantity of unskilled labor it wants to hire, as determined by its labor demand schedule. At this second stage the firm also decides how much skilled labor to employ. It can draw from a pool of skilled workers, but it is assumed to face a labor

[20] The interaction between union power and wage inequality has also been explored for the US by, e.g., Card (1992) and Freeman (1993).

[21] Acemoglu *et al.* (2000) provide a brief survey of the literature.

[22] Although sub-optimal as compared with efficient bargains, the right-to-manage model appears to be a good description of wage bargains –especially once high skill workers are excluded– in Europe in general, and in Spain in particular (see Layard *et al.*, 1991, and Bentolila and Dolado, 1994, respectively).

supply schedule, so that it has to pay a higher wage the higher the amount of skilled labor it wants to hire.

As usual, we solve backwards: first for skilled and unskilled labor demands, and then for the unskilled wage, which is determined by bargaining given agents' knowledge of those labor demand curves.

The firm maximizes real profits, π, subject to a Cobb-Douglas production function, an isoelastic product demand curve, and an isoelastic skilled labor supply curve, respectively:[23]

$$\begin{aligned} \pi &= PY - W_u N_u - W_s N_s && (2) \\ Y &= A N_u^{\alpha} N_s^{1-\alpha} && (3) \\ P &= Y^{-\frac{1}{\eta}} && (4) \\ N_s &= \delta^{-1} W_s^{\delta} && (5) \end{aligned}$$

where P is the firm's product real price, in terms of an aggregate price index, Y is output, A is total factor productivity, and N_s and N_u are, respectively, skilled and unskilled labor, which are paid real wages W_s and W_u. All coefficients are positive: α captures the unskilled labor intensity in production, η the price elasticity of product demand, and δ the wage elasticity of skilled labor supply. We assume: $0 < \alpha < 1$ and $\eta > 1$. The parameter A could also be interpreted as including a predetermined input like capital and, in general, we might allow for decreasing returns to labor –i.e. the sum of the coefficients on N_s and N_u being less than one–; constant returns are just assumed for simplicity.

The first order conditions for the optimal choice of skilled and unskilled labor are given by:

$$\begin{aligned} N_s &= \left(\frac{\delta}{1+\delta} (1-\alpha) \kappa A^{\kappa} N_u^{\alpha\kappa} W_s^{-1} \right)^{1/(1-(1-\alpha)\kappa)} && (6) \\ N_u &= \left(\alpha\kappa A^{\kappa} N_s^{(1-\alpha)\kappa} W_u^{-1} \right)^{1/(1-\alpha\kappa)} && (7) \end{aligned}$$

where $\kappa \equiv 1 - 1/\eta$ captures the degree of competition in the product market. Operating on (2)-(7) we can obtain expressions for the optimal N_s and N_u as functions of the unskilled wage level W_u alone, which are used as constraints on the bargaining game.

[23] Note that the parameters δ and γ (with no subindex) used in this section are unrelated to the same parameters (typically with subindices) used in preceding sections. The same is true of parameter β in the next subsection.

5.2 Wage bargaining

We assume unskilled workers are represented by a labor union, which bargains with the firm so as to maximize the Nash product:[24]

$$\Omega = (U_u - \widetilde{U}_u)^{\beta}(\pi - \widetilde{\pi}) \tag{8}$$

where U_u and β denote, respectively, the utility level and the bargaining power of the union, and $\widetilde{U}_u$ and $\widetilde{\pi}$ denote the agents' reservation values. $\beta \geq 0$ is a natural restriction.[25]

Labor union utility can be represented as being utilitarian, in the following way:[26]

$$U_u = N_u V_u[W_u] + (L_u - N_u)\widetilde{V}_u$$

where L_u is union membership and N_u the number of employed members. $V_u[W_u]$ and $\widetilde{V}_u$ respectively denote utility obtained by employed and unemployed union members. The latter may be characterized as:

$$\widetilde{V}_u = \widetilde{V}_u[u_u B_u + (1 - u_u)\widetilde{W}_u)]. \tag{9}$$

In other words, it depends on the variables determining "expected" income, namely: unskilled workers' unemployment rate, u_u, the wage they can obtain elsewhere, $\widetilde{W}_u$, and the real unemployment benefit level, B_u.

Assuming $\widetilde{U}_u = L_u \widetilde{V}_u$ we can rewrite equation (8) as follows:

$$\Omega = \left((V_u[W_u] - \widetilde{V}_u)N_u\right)^{\beta}(\pi - \widetilde{\pi})$$

This objective function is maximized subject to the first order conditions (6) and (7). Setting the firm's statu quo point, $\widetilde{\pi}$, to zero for simplicity, we obtain the first order condition for W_u:

$$\beta \frac{V_u' W_u}{V_u - \widetilde{V}_u} - \beta - (1 + \beta)s_u = 0$$

where $V_u' \equiv dV_u/dW_u$ and $s_u \equiv W_u N_u/\pi$.

With the additional assumption of isoelastic utility,

$$V_u = \gamma^{-1} W_u^{\gamma}$$

[24] We are therefore assuming away any strategic interactions among agents, which may give rise to alternative equilibria.

[25] The bargaining framework we assume follows Layard, Nickell, and Jackman (1991).

[26] This corresponds to maximizing the utility of the median voter once we assume that layoffs of unskilled workers are by random assignment.

with $\gamma > 0$, the preceding equation can be rewritten in terms of a utility markup (M_u):

$$M_u = \frac{V_u - \widetilde{V}_u}{V_u} = \frac{\beta\gamma}{\beta + (1+\beta)s_u} \tag{10}$$

where $s_u = \frac{\alpha\kappa}{1-\alpha\kappa-(1-\alpha)\kappa\delta/(1+\delta)}$. It is immediate from (10) that in this case $M_u \geq 0$, so that the participation constraint is satisfied.

Comparative statics are straightforward:

$$\frac{\partial M_u}{\partial \beta} > 0; \frac{\partial M_u}{\partial \gamma} > 0; \frac{\partial M_u}{\partial \alpha} < 0; \frac{\partial M_u}{\partial \delta} < 0; \frac{\partial M_u}{\partial \kappa} < 0; \frac{\partial M_u}{\partial \widetilde{V}_u} > 0 \tag{11}$$

In other words, the markup is higher: the lower the unskilled labor intensity in production (α); the higher the union's bargaining power (β) and workers' reservation value ($\widetilde{V}_u$), and the more the union cares about wages (γ); the lower the wage elasticity of skilled labor supply (δ); and the lower the degree of competition in the product market (κ). These are all standard, except for δ. The higher δ, the less costly it is for the firm to increase its use of skilled labor, which should, *ceteris paribus*, hurt unskilled workers' wages.

Let us now turn to the log unskilled wage and the log skill premium, for which our empirical model is estimated. Equation (10) implies that:

$$w_u \equiv \log W_u = \gamma^{-1} \log(\gamma(1-M_u)^{-1}\widetilde{V}_u). \tag{12}$$

Thus, for most parameters, the effects on M_u carry through to W_u: $sign\left(\frac{\partial w_u}{\partial \lambda}\right) = sign\left(\frac{\partial M_u}{\partial \lambda}\right)$, for $\lambda = \{\beta, \alpha, \delta, \kappa, \widetilde{V}_u\}$. The exception is the preference parameter γ: although it might be natural to expect the positive sign in (11) to also carry through, the actual effect is ambiguously signed. This happens because, due to the nonlinear relationship between W_u and M_u induced by the isoelastic preference specification, an increase in γ has two types of effects: it raises all the level terms but it also reduces the exponent (γ^{-1}).[27] In any event, in our numerical simulations mentioned below the positive sign is always obtained.

Turning now to the skill premium, the combination of conditions (6) and (7) yields a very simple expression for the relative skilled-unskilled wage bill:

$$\frac{W_s N_s}{W_u N_u} = \frac{1-\alpha}{\alpha} \frac{\delta}{1+\delta}$$

Clearly, this relative total remuneration does not depend on union activity. It depends on technology and on the elasticity of skilled labor supply. The skill premium does however depend on union activity, because there is a tradeoff between

[27] Note that, while we have not specified a functional form for $\widetilde{V}_u$, it would be natural to use the isoelastic one: $\widetilde{V}_u = \gamma^{-1}[u_u B_u + (1-u_u)\widetilde{W}_u)]^{\gamma}$.

skilled-unskilled relative wages and relative employment or –given the labor forces– unemployment, and the union cares about such a tradeoff.

From conditions (6) and (7) plus the labor supply curve, we get the following expression for the skill premium as a function solely of W_u:

$$\frac{W_s}{W_u} = \left(\frac{1-\alpha}{1+\delta}\alpha^{\alpha\kappa}\delta^{2-(1+\alpha)\kappa}\kappa A^{\kappa}W_u^{-(1+\delta(1-\kappa))}\right)^{1/(1-\alpha\kappa+\delta(1-\kappa))}$$

From this expression plus the solution for w_u in (12), we can compute the effects of the parameters on the log skill premium, $\omega_s \equiv w_s - w_u$. The parameters β, γ, and $\widetilde{V}_u$ appear only through W_u, and so their effects are oppositely-signed as those on W_u. The other parameters turn out to have ambiguously-signed effects. This is due to the Cobb-Douglas production function plus the positive elasticity of skilled labor supply. Thus, we have carried out numerical simulations with $0 < \alpha < 0.5$ (as a way to distinguish unskilled from skilled labor) and parameter values which satisfy the appropriate restrictions.[28] For κ, α, and δ, depending on the parameter set, we get positive or negative effects, so that we cannot discard either. Perhaps the most unusual result we get is that skilled-biased technological change (a lower α) might in some cases reduce the skill premium.

Given the definition of reservation utility in equation (9), an increase in the unemployment rate prevailing among unskilled workers, u_u, would lower $\widetilde{V}_u$ and W_u, thus raising ω_s. If we had considered a reservation utility level for the skilled, then it would be natural to expect that an increase in the unemployment rate among skilled workers (u_s) would lower the reservation value, thus lowering the skill premium.[29]

The model we have presented is very stylized. For instance, the Cobb-Douglas assumption imposes a unit elasticity of substitution between labor types, and some of the results are specific to this assumption. Additionally, our model is static, thereby neglecting any forward-looking behavior or any dynamics in membership or employment. It also means that we ignore the influence of factors like union bargaining power on the dynamic response of firms regarding, for instance, technology choice. Moreover, we have not considered the capital stock in the production function, and have thus ignored a potentially important source of wage inequality arising from capital-skill complementarity (see Krusell *et al.*, 1997).

Nevertheless, the model provides us with a framework for understanding the determinants of earnings and returns to skill. We therefore use it in the empirical section below as a guide for the choice of variables and for the interpretation of the signs obtained. Lastly, note that, by providing a single predicted value for the wage of each type of worker, the model leads to the interpretation of conditional variances of wages given skill as arising from unobserved heterogeneity within labor-type groups.

[28] Namely: $\beta \geq 0$, $\gamma > 0$, $\delta > 0$, $0 \leq \kappa \leq 1$, $\widetilde{V}_u > 0$. A is taken as a scale variable and set to 1.

[29] Considering capital would also imply that the wage markup would depend on the ratio of the firm's product demand relative to its capital, see Layard et al. (1991).

6 The determinants of earnings and returns to skill and experience

6.1 Basic earnings and returns to skill

As mentioned before, the first stage provides us with estimates for the conditional means and variances of basic earnings (3 firm size classes), returns to junior college and college (2 firm size classes each), and returns to potential experience. For each of these 8 variables we have 56 estimated coefficients (i.e. 8 sectors times 7 years). The second stage consists of regressing these coefficients on a set of national and sectoral economic variables. We estimate the following type of regression for each set of coefficients j $(j = 1, ..., 8)$:

$$\begin{aligned}\widehat{\beta}_{jts} = {} & f(Union\ coverage_{ts}, Firm\text{-}level\ coverage_{ts}, Public\ employment_{ts}, \\ & Hiring\ rate_{t-1,s}, Long\text{-}term\ unemployment_{t}, \\ & Unskilled\ unemployment_{t-1}, Skilled\text{–}Unskilled\ unemployment_{t-1}, \\ & R\&D_{t-1,s}, University\ degree\ population_{t}, Population\ 20\text{-}24_{t}, Sector_{s})\end{aligned} \tag{13}$$

The regressors in equation (13) are intended to capture the determinants of earnings, as suggested by our theoretical model in Section 5. For each variable, we will discuss both how it relates to the theory and its estimated effect. In order to capture any variation in the estimated coefficients coming from forces left out of the model, we also include a few additional variables, listed below.

We start by presenting the results for the conditional means of basic earnings and returns to skill, leaving the discussion of returns to experience and conditional variances to subsequent sections. The estimates, from weighted least squares, are shown in Table 5.[30]

There are five blocks of variables, measuring: time-invariant sectoral characteristics, union bargaining power, reservation utility levels, technological change, and labor supply.[31] Let us take them in turn.

(i) Time-invariant sectoral characteristics regarding technology (α), the degree of product market competition (κ), workers' bargaining power (β), etc. are represented by sectoral dummies. These may, however, also capture the fact that our measure of skill through the number of years of education may be a poor one, which could be refined if we observed the actual type of studies completed. In general, college graduates may correspond to different occupations in different sectors. It is more likely, for instance, to find college graduates with narrow job opportunities (e.g. with degrees

[30] OLS estimates are very similar and are available from the authors upon request.

[31] Details on definitions and sources are given in Appendix 1. The evolutions of sectoral and aggregate variables, and their sectoral breakdown, are shown in Tables A2 and A3, respectively.

in Philosophy) performing less skilled tasks in Other services than in Transportation and public utilities (cf. Figure 10, panel (b)). As a result, sectoral dummies may also capture skill composition effects.

The last line in Table 5 presents the goodness-of-fit statistic R^2 for regressions of the first-stage coefficients on sectoral dummy variables alone. These statistics are relatively high, which suggests that most of the variation in the dependent variables is of a cross-section rather than a time-series nature. Since, for the above reason, sectoral dummy variables are included alongside economic variables in these regressions, the latter not only capture any time-series variation but they also complement and/or compete with the dummies in explaining the cross-section variation. This fact, coupled with our having data for only 7 years, may help explain why few economic variables attain high statistical significance.

Table 5 also shows the R^2 statistics for regressions with both sectoral dummies and a time trend. The full results of this specification are reported in Table A4, in which the trends are significant for all variables but one (returns to junior college in small firms). In several sectors, the R^2 statistics show that the trend already accounts for almost as much of the variation in the dependent variable as all the economic variables included together. Nevertheless inclusion of economic variables obviously allows for an economic interpretation of the results which is precluded in the case of the trend, although, given lack of precision of the estimated effects, we will focus on their signs rather than their relative magnitudes.

(ii) Union bargaining power (β) is meant to be captured by three sectoral variables.[32] *Union coverage* is the share of employees covered by any type of collective agreement. As predicted by the model, it is found to raise basic earnings and to lower returns to skill or, in other words, to reduce wage dispersion.[33] The second finding is more robust for returns to college than for returns to junior college.

In Spain, wage rates agreed to in sectoral bargains are in effect binding floors for any lower-level bargains. Consequently, the *share of employees covered by firm-level agreements* is expected to raise wages further, and our estimates for basic earnings confirm this prediction. It also raises returns to skill, a result which can be interpreted as follows. Individual firms have essentially no say in sectoral bargains. When there is a firm-level bargain, however, management will try to link wages more tightly with productivity levels. This can still be mutually advantageous: less skilled workers get more than the corresponding sectoral-agreement wage (which serves as their reservation level), while firms manage to mitigate wage compression typically imposed by sectoral agreements.

Thirdly, unions are more powerful in the public sector, but this should be largely

[32] They could also capture the parameter determining the relative weight of wages vis-a-vis employment in union utility (γ).

[33] Empirically, unions have been found to reduce wage dispersion also in the US (e.g. Freeman, 1980,1993; and Card, 1992) and Canada (Lemieux, 1998).

captured by the union coverage variable. Thus, the empirical finding in Table 5 that the *share of employees working in the public sector* reduces basic earnings could be capturing the following compensating differential: even non-tenured public sector employees –the ones in our sample– have higher job security than private sector employees, and so they should earn lower wages. On the other hand, the public employment share is found to have a positive effect on returns to skill, which may reflect public-sector pay schedules aimed at recruiting/retaining skilled workers with attractive alternative opportunities in the private sector, for whom job stability may be less important.

(iii) The reservation utility level ($\widetilde{V}_u$) is represented by several variables. First, when the *hiring rate* –as a share of sectoral employment– increases, prospects for incumbent employees improve, and so their wages should go up. We include this variable rather than the sectoral unemployment rate because the hiring rate, as a flow, may be a better indicator of labor market tightness (see Blanchard and Katz, 1997). The estimated positive effect on both basic earnings and returns to skill accords with our expectations.

The existing literature has pointed out that there are often negative effects of unemployment duration on employability (due to loss of skill, disenfranchisement from the labor force, discrimination, etc.). Thus, the higher the *long-term unemployment share* (1 year or longer) in total unemployment, the better the prospects for current employees if they became unemployed, and so the higher their wages. However, this effect may not be the same for all employees: if the cause of the negative duration dependence is loss of skill, then the average skill in the unemployed population falls, which may decrease competition faced by skilled workers while increasing competition faced by unskilled workers. Our finding in Table 5 that the long-term share does reduce basic earnings while raising returns to skill suggests that latter effect dominates the former.

The last set of variables representing reservation utility are the *unskilled unemployment rate*, in the equation for basic earnings, and the corresponding *skilled–unskilled unemployment rate differentials*, in those for returns to college and junior college. For all of these variables we expect a negative effect, which is corroborated by our estimates.

(iv) Technological progress is represented by *sectoral R&D expenditures* as a share of value added. By increasing overall productivity, R&D should raise all earnings. If it is largely skill-biased, then it would reduce the intensity of unskilled relative to skilled labor in production (α) and we would expect a negative effect on basic earnings and a positive one on returns to skill, although we have shown in Section 5 that this need not happen.

Our estimates in Table 5 indicate that R&D intensity raises basic earnings, except at small firms. This is consistent with the hypothesis that labor unions redistribute the gains from improved technology to all workers and with the empirical findings in van Reenen (1993) for the UK. On the other hand, little uniformity is found for returns to skill: returns to college in small firms increase but there is no effect in medium-large ones, returns to junior college fall in the latter firms but there is no effect in small ones. Although compatible with the theory, these findings are somewhat surprising, and we can think of two potential reasons for them. The first one is that our measure of R&D is quite noisy and more aggregated than the other sectoral variables. The second reason is that R&D expenditures may mean very little in a country like Spain, that is more an adapter than a producer of technology. Indeed, Spanish R&D expenditures are very small (3% of value added in our sample period), so that most technological progress is generated by imported patent licences or is embodied in imported capital goods.[34]

(v) We do not have any empirical measure for the wage elasticity of skilled labor supply (δ). However, we do control for such supply, as is typical in the recent literature on skill premia, by including as a regressor the *share of the population with a university degree*. By making skilled labor more abundant, this share should lower returns to skill. In fact, we do not find any effect on returns to junior college, while the expected negative effect is present for returns to college, though only in small firms. The latter is consistent with the composition effects we mentioned before, which we will now discuss further.

Some of the previous findings deserve a joint discussion. Table 5 indicates that firm-level coverage of wage bargains raises returns to skill except for college graduates working for small firms. We believe this is related to our hypothesis, advanced in section 4.1, that the composition of skilled labor may differ across firm size classes. In particular, the skills of college graduates are more likely to be heterogeneous in small than in large firms. Several of our estimates give support to this idea. For instance, according to our first-step estimates the variance of college earnings is lower the larger the firm (Section 4.2). And the second-step estimates indicate that a larger proportion of the aggregate population with a university degree reduces the average and raises the variance[35] of returns to college in small firms, but not in large ones.

Such differential heterogeneity could be the result of two factors. One is measurement error. We have aimed at measuring skill through the occupational groups most clearly linked to educational levels. Thus, one possibility is that small firms are more likely than large firms to employ college graduates to carry out tasks not requiring high skills[36] while reporting, for Social Security purposes, these workers as belonging to college-degree occupations.

An alternative, more compelling story is that employees at larger firms are more productive and hence command higher wages in the labor market. This is the leading explanation of the size wage effect according to Idson and Oi (1999). This may happen because larger firms are able to better screen job applicants, possibly due to economies

[34] Torres (2000) finds a similar lack of significance of R&D expenditures in trying to account for skill-biased technological progress in Spanish manufacturing.

[35] See Section 6.3.

[36] Typically, workers with college degrees with relatively low market demand.

of scale in screening, and to attract and retain more capable workers through offering better opportunities and career ladders, due to their larger capital or other advantages.

Whatever the actual source, the higher ability of skilled workers in large firms would help account for two of our findings. First, if firm-level bargaining allows firms to associate wages more closely with productivity levels, then this type of bargaining should benefit college graduates working in large firms but could easily hurt those in small firms. Second, skill-biased technological change, to the extent that it is present, should benefit skilled workers in large firms, but not necessarily in small ones, helping to account for the diverging pattern of returns to skill in the two size classes over time.

We should report that we also tried with a few other variables suggested by either our model or recent research on wage inequality. First, as a measure of the degree of competition in the market (κ) we included the international trade balance and the import penetration rate by sector (for very broad sectors, due to lack of disaggregated data). Similar measures have been employed in other studies, mainly for the US, as an exogenous force creating competition against domestic unskilled labor from less developed countries and also reducing the demand for manufacturing goods. Secondly, returns to skill should be related to the capital-labor ratio if capital and skills are complementary factors, so we included such a ratio at the sectoral level (both for public and private capital stocks). Lastly, another potential source of an increase in the demand for skill is the shift from the primary and secondary sectors towards services. Thus, we also included the share of services in national GDP. None of these variables was significant at all, and so they are not discussed any further.

6.2 Returns to experience

For returns to experience, we estimate the second stage regression on the composite coefficient $(\widehat{\beta}_{10ts}+2\widehat{\beta}_{11ts}Age)$ (see equation (13)). We choose a value of 35 for Age, which is a representative value, close to the average age in the sample (37.9 years old).

Our model does not address the issue of experience, so at this point our discussion must be more informal. A parsimonious specification includes, apart from sectoral dummies, the following four variables: (a) the coverage of *firm-level agreements*, whose coefficient should be positively signed if older workers carry a higher weight in unions' objective functions than younger ones (we also tried union coverage, but it was not significant at all); (b) the *hiring rate*, which should have a negative effect if the composition of newly hired employees is unbalanced in favor of younger workers; (c) the share of employees in the *public sector*, which should have a positive effect if seniority ladders are steeper in the public than in the private sector; and (d) the share of the *population of 20 to 24 years old*, which should bear a positively signed coefficient for straightforward labor supply reasons.

All of these expected signs are obtained, as shown in the last column of Table 5, except for the finding that a higher coverage of firm-level agreements tends to reduce returns to experience. This could again arise if in firm-level bargains wages are more tightly linked to productivity than at sectoral bargains and if younger cohorts of workers –as seems to be the case– possess higher skills than older ones, controlling for experience.

6.3 Conditional variances

Lastly, we also explore the relationship between economic variables and the conditional variance of earnings, i.e. the variance within skill-firm size categories. As pointed out before, first-step estimates indicate little change in variances over time, except for workers with a college education. Since for all other skill groups sectoral dummies can be expected to capture most of the differences in conditional variances, here we only estimate a model with economic variables for college educated workers. Our theoretical model provides little guidance for this purpose, since it attributes conditional variances to unobserved heterogeneity of workers within skill-experience-firm size groups. Table 6 reports the results, in which the bottom rows show that again once sectoral dummies are included, adding economic variables does not much raise R^2 statistics over and above those obtained by simply including a time trend. The estimates indicate that higher dispersion in returns to skill is positively associated with a higher share of collective bargaining being carried out at the firm-level, with a higher sectoral hiring rate and, for small firms, with a higher share of the population with a university degree. The latter is again consistent with the potential importance of heterogeneity of college educated employees working in small firms.

7 Conclusions

In this paper we provide a detailed account of the evolution of earnings and returns to skill and experience in Spain over the 1980s, using a new matched employer-employee database of Social Security records. We employ a sample of monthly earnings for more than 30,000 male employees for the period 1980-1987.

We start with a description of the evolution of the quantiles of the earnings distribution and show that Spain conforms to the Continental European pattern, experiencing little changes in dispersion below the median, but behaves more like Anglo-Saxon countries in showing a significant increase in dispersion above the median. The more skilled workers benefited from earnings increases, mostly at the end of the period. Increases in the relative earnings of older workers are also evident over the period.

We pursue a two-stage empirical strategy. In the first stage we estimate the common component of earnings –or basic earnings– , returns to skill for college and junior college educated workers vis-à-vis unskilled workers, and returns to potential experience (age), all by sector and year. We estimate both conditional means and conditional variances, which are allowed to vary by firm size (except for returns to experience). We find that larger firms tend to pay higher wages and also a pro-cyclical evolution of earnings. Returns to skill are found to have increased over the sample period except for workers with a college degree working in small firms. We speculate that the latter finding may stem from higher heterogeneity among those workers within that size class, and find some support for this idea from our analysis of conditional variances. Returns to potential experience are found to have steadily increased over the period.

Our second stage estimation draws from a simple theoretical model of wage bargaining at firms employing skilled and unskilled labor, and operating in imperfectly competitive product markets. We assume unskilled labor bargains for its wage with the firm ex-ante, while skilled labor is supplied according to an upward-sloping curve. We find wages and returns to skill to depend on union bargaining power and reservation utility levels, technological change, the extent of product market competition, and the wage elasticity of skilled labor supply.

We then estimate the effects of empirical measures of these variables on the sector-period sets of estimates for basic earnings, returns to skill, and returns to experience. Our results suggest the following underlying forces affecting earnings inequality. Labor union activity tends to reduce inequality across skill groups, while firm-level bargaining and public employment (once sectoral coverage of collective bargaining is controlled for) tend to raise it. Long-term unemployment has an asymmetric effect, reducing unskilled workers' earnings but increasing returns to skill, thereby raising inequality. Investments in *R&D* tend to increase the earnings of most workers, with no clear effects on returns to skill, although we believe this variable provides a very poor measure of technical progress in our data. The expected tradeoff between earnings of different skill classes of workers and their respective unemployment rates is evident in the data. Probably due to the limited amount of variability across sectors and over time, economic variables do not to have a large amount of explanatory power; in particular they explain slightly more than a simple specification with just sectoral dummies and a linear trend.

We also find increases in dispersion, in terms of conditional variances, within the group of college educated workers. Such dispersion depends positively on the share of collective bargaining being carried out at the firm-level, on the share of educated workers in the population, and on the state of the cycle.

Our estimates also indicate that returns to potential experience increased over the period. They are found to depend positively on the share of youth in the population and the share of employment in the public sector, and negatively on the state of the business cycle.

In sum, we find that Spain experienced a non-negligible increase in earnings inequality in the 1980s, mostly in the upper half of the earnings distribution and in the second half of the decade. As in other OECD countries, returns to skill and to potential experience increased, as well as inequality among college graduates. These evolutions are found to be related to labor supply forces but also to the features of the wage bargaining system in the Spanish economy once cyclical factors are controlled for. The effects of union activity turn out not to be very well determined, but the interpretation of this result is not straightforward. It may be that union activity is not a very important factor in the evolution of wage inequality. However, there may be other explanations. For instance, union activity or bargaining power may be poorly approximated by the empirical measure we use, namely the sectoral coverage of collective bargains. Or it may be that union coverage does not show enough variability in our sample. Lastly, lack of observability of certain potentially important characteristics, like the sectoral breakdown of the types of degrees attained by workers with college and junior college education or sectoral measures of market power, led us to include sectoral dummies in our estimation. If union power varies essentially by sector, then its specific effect is bound to be very hard to disentangle from the differences already captured by the sectoral dummies.

Appendix 1. Sources and definitions

1 Individual data

Source. Panel of data from the Social Security records from 1980:12 to 1987:12 (June and December observations only), provided by the Spanish Ministry of Labor and Social Security (Ministerio de Trabajo y Seguridad Social (MTSS)). The data set is extensively described in Toharia and Muro (1990).

Sample. From a sample of men of 20 to 64 years of age we exclude workers

* in agriculture, farming, forestry, and fisheries

* with earnings below the bottom coding level in his occupation

* whose earnings have doubled from one year to the next

* living in Ceuta or Melilla (Spanish provinces in the North of Africa)

* with a missing observation for age, occupation, region, or firm identifier (deleted only in the period when one of these four variables is missing).

Once we keep the December observations only, we extract a random sample of 140,545 observations, which correspond to 32,291 workers.

Earnings. The earnings measure is the monthly taxable earnings base declared by the firm for Social Security tax purposes.

Skill. Four groups are formed from the information on occupation (grupo de tarifa). The groups are as follows: (1) College graduates (ingenieros y licenciados); (2) Junior college (ingenieros técnicos, peritos, ayudantes titulados y asimilados); (3) Medium skill (residual) (jefes administrativos y de taller, ayudantes no titulados, oficiales administrativos, subalternos, auxiliares administrativos, oficiales de 1^a y 2^a, oficiales de 3^a y especiales); and (4) Unskilled (peones).

Economic sector. Sectors are grouped in the following eight: Mining (8); Construction (1); Manufacturing (2); Transportation and public utilities (3); Wholesale and retail trade (4); Finance, insurance, and real estate (5); Hotels and Catering (6), and Other services (7).

Table A1 provides the frequencies of the individual variables for the sample used in the econometric estimation.

2 Aggregate and sectoral variables

2.1 Aggregate variables

Long term unemployment. Unemployed for a year or more (share).

Unemployment rates by skill: Unskilled (no studies), Analfabetos y sin estudios, Junior college (3-year university degree), Estudios de nivel anterior al superior, College (5-year university degree), Estudios superiores.

Population aged 20-24 years old. Share of population aged 16 to 64.

Population with a university degree (includes college and junior college). Share of population aged 16 to 64.

Source: Encuesta de Población Activa (EPA) of the Instituto Nacional de Estadística (INE). Descriptive statistics are provided in Table A2.

2.2 Sectoral variables

Coverage of collective agreements. (a) Numerator: number of workers covered, by starting year of effectiveness of the agreement, broken down by the 8 sectors listed above. It includes both firm-level and wider agreements. Period: (i) For 1980 the sectoral breakdown and the data for Cataluña and País Vasco are missing, and so this year is omitted. (ii) 1981 and 1982 figures have been corrected because data for Cataluña are missing. The original data are multiplied by the factor (1/0.9189), using the fact that Cataluña had, in 1983, 8.11 percent of the total number of workers covered in Spain. (iii) The original 1983 observation for the sector of Finance, insurance, and real estate was artificially low, due to partial official recording of coverage of the main collective agreement, because it was signed originally by only one of the two main unions and many workers adhered to it with a lag. Thus, we use instead the average of the 1982 and 1984 values. Source: Boletín de Estadísticas Laborales (MTSS). (b) Denominator: Employees per sector. Source: EPA. Due to different sources for the numerator and the denominator, the ratio is above 1 for some sectors. This may also arise from double counting: for instance, if there are firm-level agreements in a sector with a sector-wide agreement, it might happen that those reporting the coverage of the latter do not subtract the number of workers covered by the former. Sectors: Other services excludes subsectors in which the vast majority of workers are tenured public employees (Spanish classification CNAE-1974 subsectors 91, 93, 94, and 99).

Coverage of firm-level collective agreements. As in union coverage, but using as the numerator only the number of workers covered by agreements signed at the firm level.

Hiring rate. Ratio of hires to employed workers (Colocaciones registradas divided by ocupados). Two sectors, Trade and Hotels, are considered jointly because the numerator cannot be disaggregated. Source: Estadísticas de Empleo, Boletín, Instituto Nacional de Empleo, for the numerator and EPA for the denominator.

Percentage of employees in the public sector. Broken down by the 8 sectors listed above. Source: EPA.

Research and development expenditures. Expenditures divided by value added (Total gastos intramuros en I+D divided by valor añadido). Broken down by 6 sectors, e.g. considering Trade and Hotels together, and Finance, Insurance, Real State and Other Services together. Source: numerator from Estadística sobre las actividades en investigación científica y desarrollo tecnológico, INE, and denominator from Banco de España.

Table A1. Frequencies of individual variables

	Number	Percentage
Observations	140,545	100.00
Non-censored	112,828	80.28
Censored	27,717	19.72
of which:		
– Bottom coded	725	0.52
– Top coded	26,992	19.21
Workers		
Total	32,291	100.00
Observed:		
1 year	6,159	19.07
2 years	4,143	12.83
3 years	3,103	9.61
4 years	2,553	7.91
5 years	2,447	7.58
6 years	2,858	8.85
7 years	11,028	34.15
Individual characteristics		
Cohort (avg. age = 37.9 yrs. old)		
1916-29	11,346	8.07
1930-39	28,897	20.56
1940-49	37,647	26.79
1950-59	49,778	35.42
1960-67	12,877	9.16
Skill		
Unskilled	14,915	10.61
Medium skilled	110,353	78.52
Junior college	4,623	3.29
College	10,654	7.58

Table A1. Frequencies of individual variables (contd.)

	Number	Percentage
Firm characteristics		
Sector		
Mining	11,285	8.03
Construction	17,217	12.25
Manufacturing	45,020	32.03
Transportation and public utilities	12,739	9.06
Wholesale and retail trade	19,285	13.72
Finance, insurance and real estate	13,322	9.48
Hotels and restaurants	5,304	3.77
Other services	16,373	11.65
Size (number of employees)		
Up to 100	75,175	53.49
Between 101 and 1,000	41,285	29.37
More than 1,000	24,085	17.14
Year (no. of workers observed)		
1981	19,424	13.82
1982	19,448	13.84
1983	19,488	13.87
1984	19,288	13.72
1985	19,610	13.95
1986	21,067	14.99
1987	22,220	15.81

Table A2. Sample statistics of aggregate economic variables (%)[1]

	Mean	Stand. dev.	Value in 1981	Value in 1987	Change 1981-87
Long-term unemployment	53.04	6.62	40.14	61.96	21.82
Unskilled unemployment rate (t-1)	15.64	3.93	10.70	20.78	10.08
Junior coll. – Unskilled unempl.(t-1)	-1.65	2.49	-0.44	-5.13	-4.69
College – Unskilled unempl.(t-1)	-1.56	2.63	-1.05	-5.33	-4.28
Population with university degree	8.35	0.91	7.25	9.72	2.47
Population aged 20-24 years old	13.00	0.30	12.60	13.50	0.84

Notes:
[1] Population aged 20-24 years old is used as a ratio (as opposed to percentages) in the empirical estimation.

Table A3. Sample statistics of sectoral economic variables (%)[1]

	Mean	Standard deviation	Value in 1981	Value in 1987	Change 1981-87
Hiring rate (t-1)					
1. Construction	56.2	16.8	43.5	84.0	40.5
2. Manufacturing	16.9	4.9	11.7	25.3	13.6
3. Transport. and public utilities	7.7	2.4	5.4	11.7	6.4
4. Trade	15.5	6.0	9.4	24.8	15.4
5. Finance, insurance, real state	11.8	5.8	6.9	21.4	14.5
6. Hotels and catering	15.5	6.0	9.4	24.8	15.4
7. Other services	10.1	5.9	4.4	18.9	14.5
8. Mining	7.9	2.9	5.0	12.6	7.6
Union coverage					
1. Construction	74.3	18.9	33.4	82.8	49.4
2. Manufacturing	114.1	14.9	82.5	121.9	39.4
3. Transport. and public utilities	78.5	6.7	64.9	83.8	18.9
4. Trade	96.7	18.1	60.2	96.0	35.8
5. Finance, insurance, real state	107.8	11.8	128.0	98.7	-29.3
6. Hotels and catering	89.3	14.2	65.7	86.8	21.1
7. Other services	40.3	11.0	22.5	44.8	22.3
8. Mining	103.4	6.5	95.6	104.4	8.8
Firm-level coverage					
1. Construction	1.3	0.7	2.7	1.2	-1.5
2. Manufacturing	21.0	1.4	18.4	20.0	1.6
3. Transport. and public utilities	48.8	3.2	44.6	49.9	5.3
4. Trade	4.9	0.5	5.3	4.1	-1.2
5. Finance, insurance, real state	7.5	2.0	9.1	5.6	-3.5
6. Hotels and catering	3.3	0.5	3.3	2.7	-0.6
7. Other services	7.3	1.9	3.4	8.5	5.1
8. Mining	27.9	2.4	31.8	26.8	-5.0

Table A3. Sample statistics of sectoral economic variables (%) (continued)[1]

	Mean	Standard deviation	Value in 1981	1987	Change 1981-87
R&D expenditure (t-1)[2]					
1. Construction	0.8	0.2	0.7	0.7	0.0
2. Manufacturing	8.1	2.2	6.2	11.4	5.3
3. Transport. and public utilities	2.3	0.5	1.5	2.9	1.4
4. Trade	0.0	0.0	0.0	0.0	-0.0
5. Finance, insurance, real state	0.5	0.2	0.4	0.9	0.5
6. Hotels and catering	0.0	0.0	0.0	0.0	-0.0
7. Other services	0.5	0.2	0.4	0.9	0.5
8. Mining	10.8	1.5	9.5	13.4	3.9
Public employment share					
1. Construction	6.4	2.5	5.0	4.8	-0.1
2. Manufacturing	5.6	0.8	4.8	4.9	0.2
3. Transport. and public utilities	49.7	2.7	45.4	47.4	2.0
4. Trade	2.1	0.6	1.7	1.6	-0.1
5. Finance, insurance, real state	3.6	0.8	3.0	3.6	0.6
6. Hotels and catering	2.1	0.6	1.6	1.7	0.1
7. Other services	59.5	1.8	58.0	59.9	1.9
8. Mining	10.0	0.6	9.2	10.2	1.0

Notes:
[1] The following variables are used as ratios (as opposed to percentages) in the empirical estimation: Union coverage, Firm-level coverage.
[2] 0.0 means lower than 0.05 %.

Table A4. Second stage estimates with sectoral dummies and trend only[1]

	Basic earnings			Returns to junior college		Returns to college		Rets. to expe-rience
	Small	Med.	Large	Small	Med-lge.	Small	Med-lge.	
Constant	10.261	10.481	10.501	0.658	0.546	0.691	0.945	0.008
	(357.60)	(349.77)	(339.01)	(9.43)	(8.99)	(24.47)	(22.53)	(31.59)
Cons-	0.595	0.440	0.540	-0.017	0.222	0.024	0.075	-0.006
truction	(21.05)	(14.81)	(17.03)	(0.38)	(7.07)	(0.83)	(1.30)	(24.07)
Transpt.	0.078	0.135	0.206	0.435	0.168	0.196	0.193	3×10^{-4}
& p. util.	(1.79)	(3.04)	(4.55)	(1.72)	(2.91)	(3.40)	(2.01)	(0.83)
Trade	-0.007	-0.095	0.006	-0.159	0.331	-0.006	0.269	0.001
	(0.23)	(2.78)	(0.17)	(4.27)	(1.77)	(0.22)	(2.72)	(3.46)
Finance,	-1.323	-1.426	-1.390	-0.150	-0.129	0.405	-0.080	0.016
ins., etc.	(20.02)	(21.41)	(20.68)	(2.75)	(3.64)	(8.42)	(1.66)	(24.48)
Hotels &	0.342	0.257	0.207	-0.331	–	-0.070	-0.252	-0.003
catering	(8.10)	(5.43)	(3.83)	(5.03)	–	(1.40)	(2.79)	(6.99)
Oth. serv.	0.039	-0.037	0.001	-0.257	-0.242	0.042	-0.362	-0.001
	(1.08)	(1.01)	(0.03)	(8.65)	(12.97)	(1.68)	(11.97)	(3.16)
Mining	-0.115	-0.047	-0.125	0.137	-0.011	0.444	-0.070	9×10^{-7}
	(2.55)	(1.01)	(2.61)	(2.61)	(0.34)	(9.65)	(1.65)	(0.00)
Trend	-0.024	-0.029	-0.020	0.017	0.036	-0.015	0.040	0.001
	(4.29)	(5.08)	(3.35)	(1.04)	(2.49)	(2.88)	(4.29)	(13.79)
R^2	0.962	0.941	0.935	0.627	0.814	0.832	0.772	0.937

Notes:
[1] The reference sector is manufacturing.

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Table 1. The distribution of real monthly earnings in 1980 and 1987[1]

	Median monthly earnings			75th-25th percentile[2]		50th-25th percentile[2]	
			Annual growth (%)				
	P50			P75-25		P50-25	
	1980	1987	1980-87	1980	1987	1980	1987
All workers	91,785	90,592	-0.19	0.540	0.615	0.269	0.278
Skill							
College	186,588	205,300	1.37	n.a.	n.a.	0.454	0.538
Junior college	137,049	153,589	1.64	n.a.	n.a.	0.317	0.296
Medium-skill	91,534	90,653	-0.14	0.499	0.562	0.252	0.262
Unskilled	67,645	65,931	-0.37	0.338	0.342	0.139	0.141
Age (years old)							
20-29	78,709	69,651	-1.73	0.465	0.410	0.200	0.167
30-44	101,341	98,628	-0.39	0.493	0.594	0.295	0.307
45-64	97,066	106,620	1.35	0.503	0.507	0.262	0.297
Sectors							
Mining	104,107	112,169	1.07	0.435	0.512	0.264	0.341
Construction	74,183	69,917	-0.84	0.368	0.332	0.146	0.128
Manufacturing	96,815	96,990	0.03	0.466	0.546	0.256	0.286
Transport. & p.u.	97,184	101,848	0.67	0.539	0.551	0.299	0.296
Trade	76,194	77,180	0.18	0.474	0.516	0.176	0.186
Finance	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Hotels	63,393	68,433	0.22	0.328	0.360	0.157	0.166
Other services	93,797	97,247	0.52	0.477	0.571	0.241	0.282

Notes:
[1] Real earnings in 1985 pesetas (deflated by the national CPI).
[2] Quantile measures refer to log earnings.

Table 2. Returns to education and experience[1]

	1980	1987	Change 1980-87
Education			
Ratio of college educated to unskilled workers median real earnings			
20-29 years old	1.82	1.94	0.12
30-44 years old	2.89	3.09	0.20
45-64 years old	3.03	n.a.	n.a.
Age			
Ratio of 45-64 to 20-29 y.o. median real monthly earnings			
College	1.74	n.a.	n.a.
Unskilled	1.05	1.19	0.14

Note:
[1]Real earnings in 1985 pesetas (deflated by the national CPI).

Table 3. Labor market variables for selected countries

A. Wage dispersion[1]

Country	Dispersion measure	1980	1987	Equivalent 7-year change[2]
France	P90/50	2.05	2.09	0.04
	P50/10	1.45	1.33	-0.12
Germany[3]	P90/50	1.63	1.63	0.00
	P50/10	1.47	1.41	-0.07
U. Kingdom	P90/50	1.72	1.89	0.17
	P50/10	1.47	1.61	0.14
U. States	P90/50	1.95	2.09	0.14
	P50/10	2.44	2.70	0.26
U. States[4]	P75/50	1.36	1.40	0.05
	P50/25	1.45	1.51	0.07
Spain	P75/50	1.31	1.40	0.09
	P50/25	1.31	1.32	0.01

B. Other labor market variables (%)[5]

Country	Population with a university degree		Share of employment in services		Unemployment rate	
	1989	Change 1979-89	1989	Change 1980-89	1989	Change 1980-89
France	11.1	3.5	63.5	8.1	9.4	3.1
Germany	11.0	5.6	51.4	5.2	3.2	6.9
G. Britain	17.4	5.4	68.5	8.8	6.1	0.0
U. States	21.5	4.9	70.5	4.6	5.3	-1.9
Spain	8.1	2.8	54.1	9.2	16.7	5.9

Notes:

[1] Wage measures: (a) $P90/50$ and $P50/10$. France: Gross annual earnings of full-time workers. Germany: Gross monthly earnings plus benefits of full-time full-year workers. U. Kingdom: Gross hourly earnings of persons paid on adult rates (the 1980 data refer to men under 21). U. States: Gross hourly earnings, computed as annual earnings divided by annual hours of work, of wage and salary workers. Source: OECD (1993). (b) $P75/50$ and $P50/25$. US: Gross hourly earnings of full-time workers. Source: Juhn *et al.* (1993). Spain: Gross monthly earnings (social security taxable rates, own calculations, see Appendix 1).

[2] Average change in a 7-year period. Original data multiplied by (7/6) in Germany and the second set of US ratios.
[3] For Germany, the first date is 1981.
[4] For the US, $P75/50$ and $P50/25$ are based on data for 1982-1988.
[5] (a) Population with college degree. France and Germany: Population aged 15 years old and older (for Germany, the change is from 1978 to 1989). G. Britain: Population aged 16-60. U. States: Population aged 18-64. Spain: Population aged 16-64. Sources for (a) and (b): Katz et al. (1995) for France, G. Britain and U. States; for Germany, Microzensus for 1978 and Statistical Yearbook of the Federal Republic of Germany (1994) for 1989; and EPA (INE) for Spain. (c) Unemployment rate. OECD-standardized rate from OECD Employment Outlook (1999).

Table 4. Labor market changes in Spain, 1980-87[1]

	Percentage shares		
	1980	1987	Change 1980-87
1. Population by group as a share of population aged 16-64 years old:			
Age			
16-19 years old	11.8	11.3	-0.5
20-29 years old	12.2	13.7	1.5
30-44 years old	37.5	38.5	1.0
45-64 years old	38.5	36.6	-2.0
Education			
Secondary or less	94.7	92.6	-2.1
of which			
– Primary or less	74.9	60.2	-14.7
– Secondary	19.8	32.4	12.6
Junior college	3.3	4.4	1.1
College	2.0	3.1	1.0
2. Sectoral shares in total employment:			
Agriculture	19.0	15.5	-3.5
Industry	27.1	24.0	-3.1
Construction	8.9	7.9	-1.0
Services	44.9	52.6	7.6
3. Unemployment rates:			
Total	11.4	20.5	9.1
Unskilled	10.7	20.2	9.5
Medium-skilled	11.7	21.1	9.5
Junior college	10.3	16.5	6.3
College	9.7	15.7	6.1

Notes:
[1] Source: Spanish Labor Force Survey (EPA), first quarter, from INE website (http://www.ine.es). Note: data not homogeneized with post-1987:1 EPA definitions.

Table 5. Determinants of basic earnings and returns[1]

	Basic earnings			Returns to junior college		Returns to college		Rets. to expe-rience
	Firm size			Firm size		Firm size		
	small	med.	large	small	med.-large	small	med.-large	
Union	-0.058	0.044	0.123	0.074	-0.033	-0.210	-0.106	
coverage(t,s)	(0.41)	(0.30)	(0.81)	(0.60)	(0.28)	(1.85)	(0.57)	
Firm-level	0.888	1.082	0.806	1.963	0.134	-0.748	1.087	-0.0221
coverage(t,s)	(1.04)	(1.25)	(0.91)	(1.03)	(0.17)	(0.87)	(0.90)	(2.98)
Public	-0.010	-0.011	-0.015	-0.028	0.001		0.014	0.0003
employm.(t,s)	(1.22)	(1.26)	(1.69)	(0.81)	(0.14)		(0.93)	(3.40)
Hiring	0.006	0.007	0.010		0.006			-0.0001
rate(t-1,s)	(3.02)	(3.14)	(4.18)		(2.03)			(5.41)
Long-term	-0.002	-0.005	-0.007			0.006	0.012	
unempl.(t)	(0.29)	(0.85)	(1.16)			(1.11)	(3.16)	
Unskilled	-0.018	-0.022	-0.020					
unempl.(t-1)	(2.35)	(2.81)	(2.46)					
College–unsk.							-0.006	
unempl.(t-1)							(0.73)	
J. coll.-unsk.				-0.013	-0.021			
unempl.(t-1)				(0.92)	(1.48)			
R&D(t-1,s)	0.001	0.023	0.023		-0.033	0.002		
	(0.11)	(1.81)	(1.77)		(1.80)	(0.21)		
University						-0.063		
degree pop.(t)						(1.91)		
Population								0.7317
aged 20-24(t)								(11.43)

Table 5. Determinants of basic earnings and returns (contd.)[1]

	Basic earnings			Returns to junior college		Returns to college		Rets. to expe-rience
	Firm size			Firm size		Firm size		
	small	med.	large	small	med.-large	small	med.-large	
Constant	10.354	10.454	10.510	0.366	0.823	1.234	0.295	-0.0789
	(52.56)	(51.73)	(51.00)	(1.15)	(3.67)	(5.77)	(1.42)	(9.91)
Construct.	0.509	0.572	0.515	0.416	-0.256	-0.189	0.237	-0.0066
	(2.45)	(2.67)	(2.33)	(1.06)	(0.88)	(0.97)	(1.04)	(3.97)
Transport.	0.329	0.527	0.922	1.142	-0.084	0.344	-0.776	-0.0060
& pub.util.	(0.76)	(1.19)	(2.03)	(0.81)	(0.20)	(1.33)	(1.12)	(1.63)
Trade	0.108	0.242	0.306	0.070	0.093	-0.144	0.476	-0.0018
	(0.57)	(1.24)	(1.52)	(0.29)	(0.54)	(0.84)	(2.39)	(1.44)
Finance,	-1.186	-1.092	-1.076	0.063	-0.330	0.308	0.087	0.0126
etc.	(6.65)	(5.96)	(5.75)	(0.28)	(1.80)	(2.01)	(0.54)	(11.04)
Hotels	0.467	0.616	0.529	-0.064	-	-0.235	-0.036	-0.0059
and cat.	(2.28)	(2.92)	(2.43)	(0.23)		(1.25)	(0.17)	(4.32)
Othr serv.	0.724	0.951	1.261	1.566	-0.541	-0.196	-1.061	-0.0189
	(1.44)	(1.85)	(2.39)	(0.76)	(0.88)	(1.18)	(1.26)	(4.31)
Mining	-0.085	-0.070	-0.072	0.129	0.113	0.468	-0.218	-0.0006
	(0.96)	(0.76)	(0.76)	(0.94)	(1.04)	(5.34)	(1.91)	(0.77)
R^2	0.964	0.944	0.944	0.655	0.801	0.853	0.799	0.947
R^2 trend + sec. dums.	0.962	0.941	0.935	0.629	0.816	0.833	0.772	0.937
R^2 sect. dummies	0.955	0.930	0.929	0.606	0.761	0.818	0.660	0.883

Notes:
[1] Weighted least squares estimates. The reference sector is manufacturing. Units: all variables in percentage terms except the share of the population of 20 to 24 years old, union coverage, and firm-level coverage.

Table 6. Regressions for the effect of college education on the conditional log-variance of earnings[1]

	Small firms	Medium-large-firms
Firm-level coverage (t,s)	–	10.022
	–	(2.59)
Hiring rate (t-1,s)	0.011	0.024
	(1.37)	(2.73)
Population with a university degree (t)	0.054	–
	(0.78)	–
Constant	1.023	-1.176
	(2.10)	(1.41)
Construction	-0.455	1.218
	(1.33)	(1.42)
Transport & public utilities	0.470	-2.53
	(2.32)	(2.39)
Trade	-0.175	1.844
	(1.79)	(2.74)
Finance, insurance and real state	-0.234	1.966
	(1.44)	(3.55)
Hotels and catering	-0.883	2.031
	(3.76)	(2.65)
Other services	-0.700	1.165
	(6.06)	(2.16)
Mining	0.281	-1.189
	(1.71)	(3.59)
R^2	0.731	0.432
R^2 sectoral dummies + trend	0.716	0.379
R^2 sectoral dummies	0.649	0.325

Notes:
[1] Weighted least squares estimates. The reference sector is manufacturing. Units: all variables in percentage terms except the share of the population of 20 to 24 years old, union coverage, and firm-level coverage.

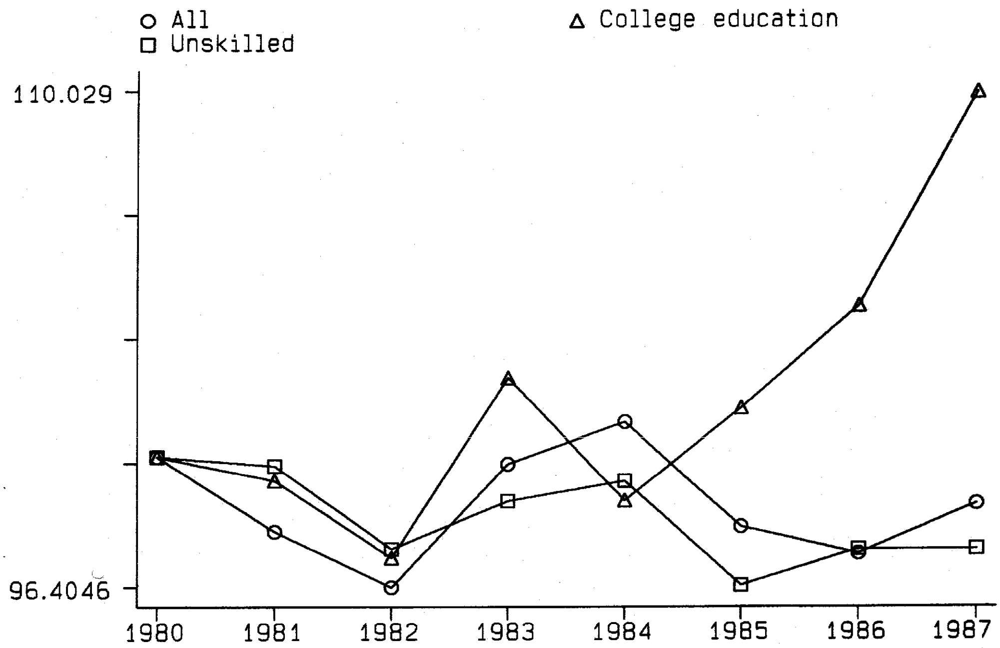


Figure 1: Median Earnings , by Skill. 1980=100

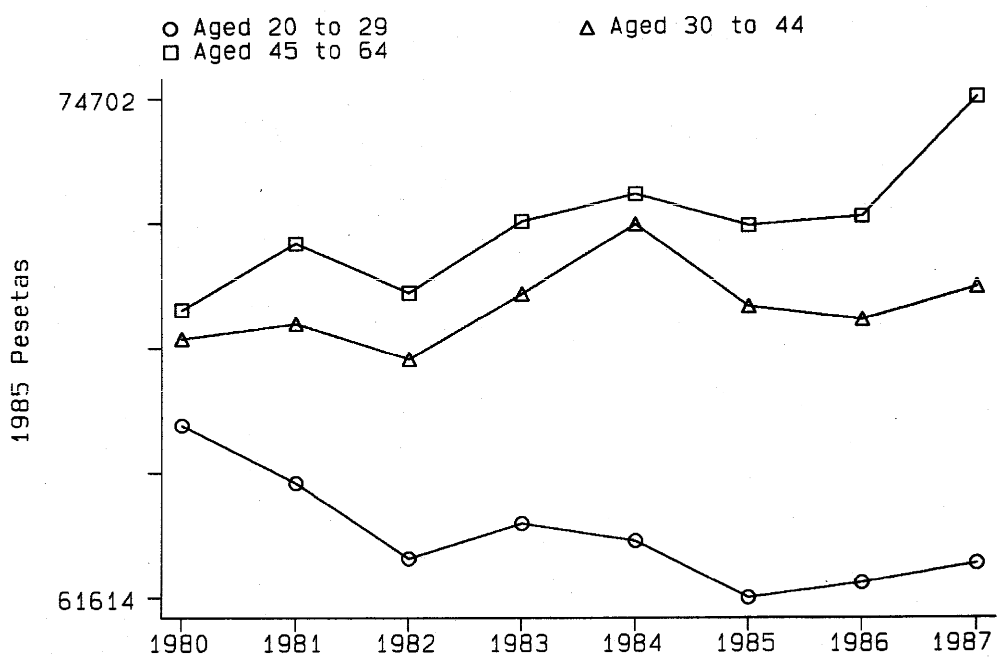


Figure 2: Median Earnings, Unskilled, by Age

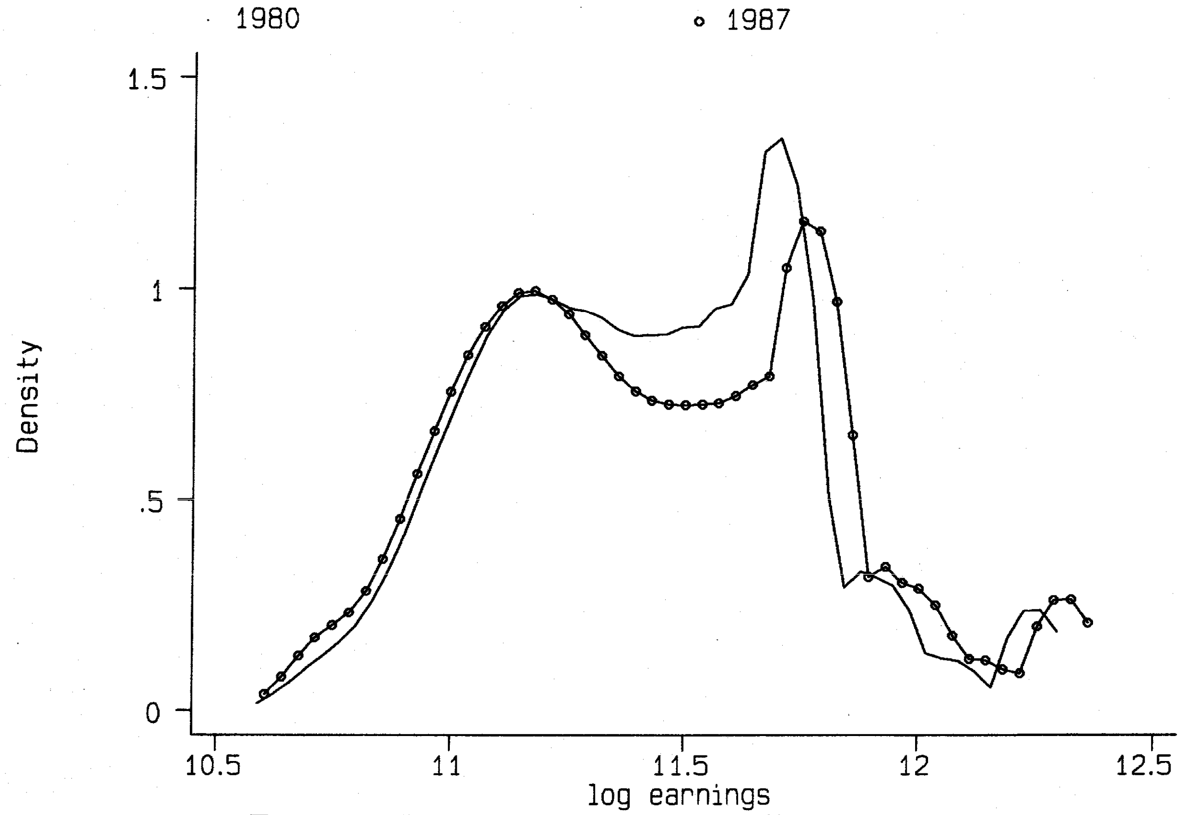


Figure 3: Kernel Density Estimates

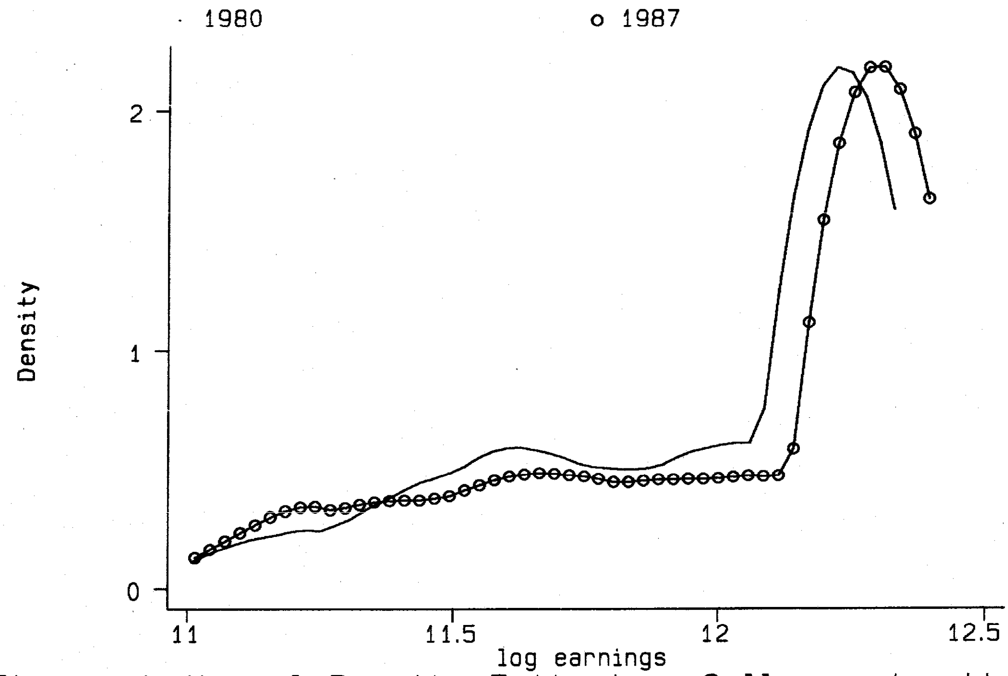


Figure 4: Kernel Density Estimates. College education

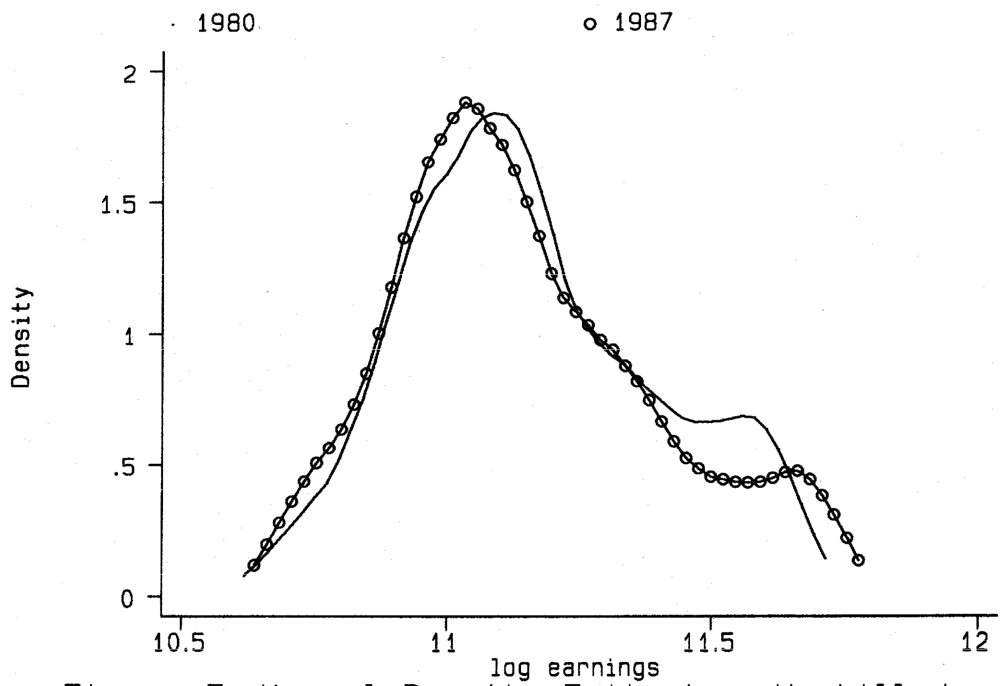


Figure 5: Kernel Density Estimates. Unskilled

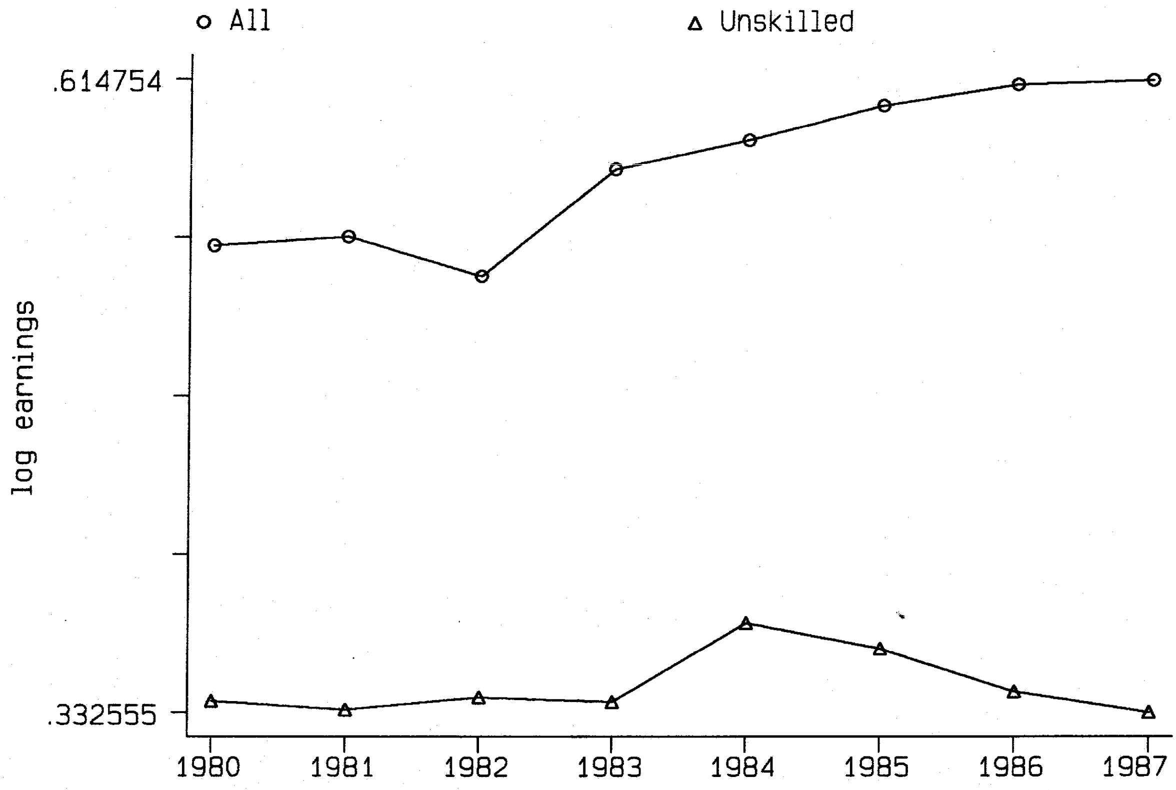


Figure 6: Interquartile Range.

Figure 7: Effect of firm size on earnings, by skill group

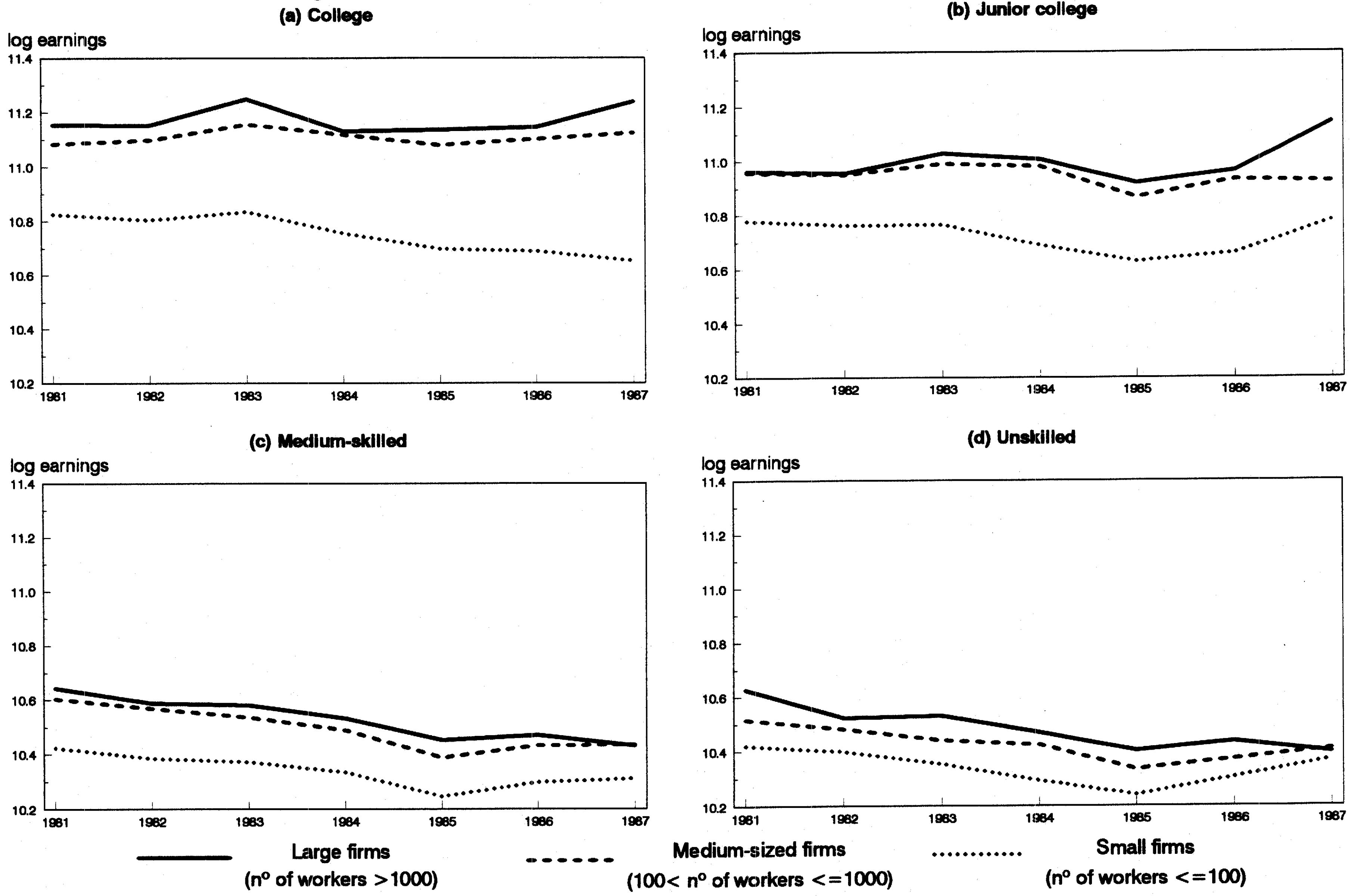


Figure 8: Evolution of the common component of earnings, by sector
Small-sized firms

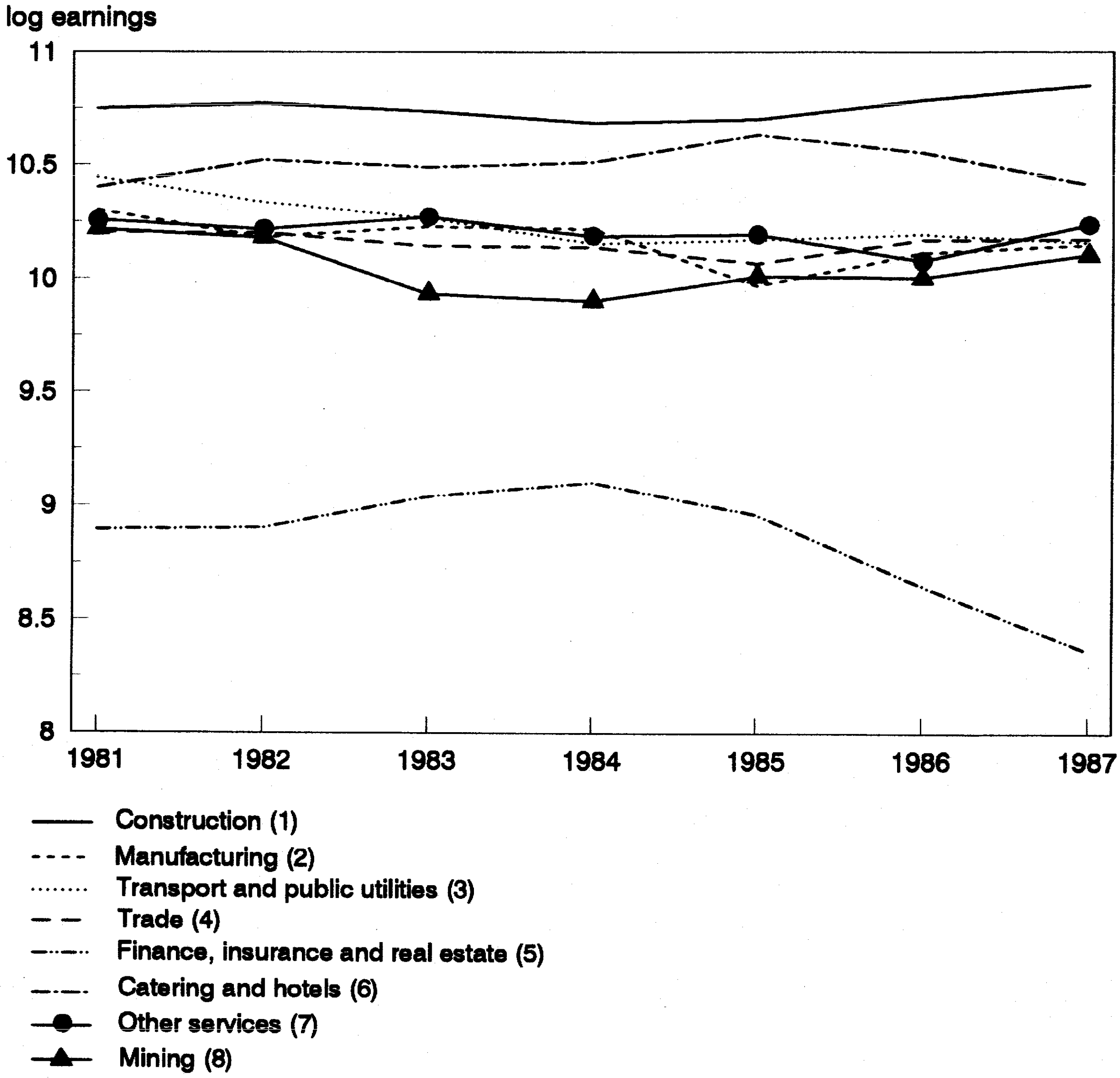


Figure 9: Returns to college
Small firms

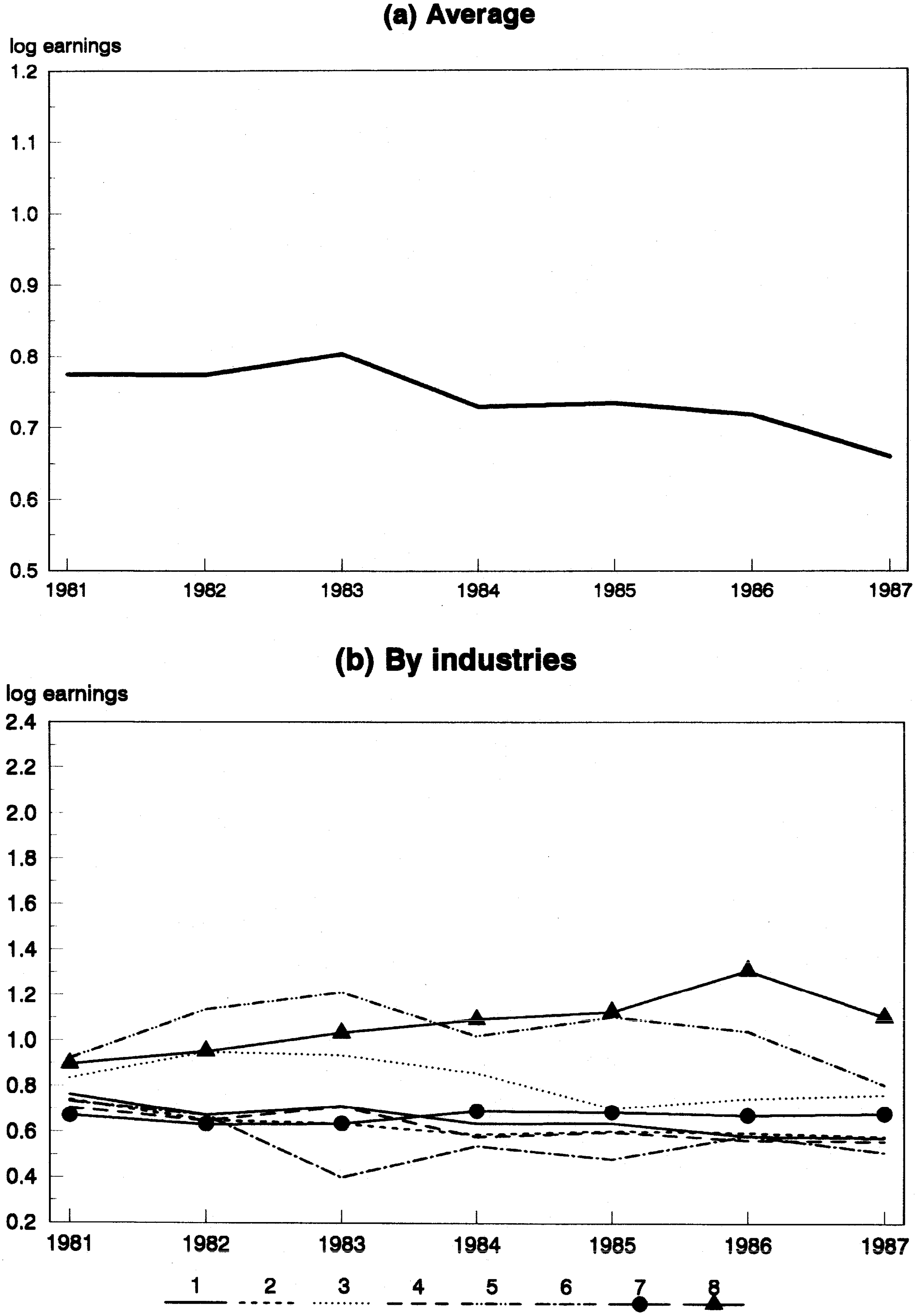
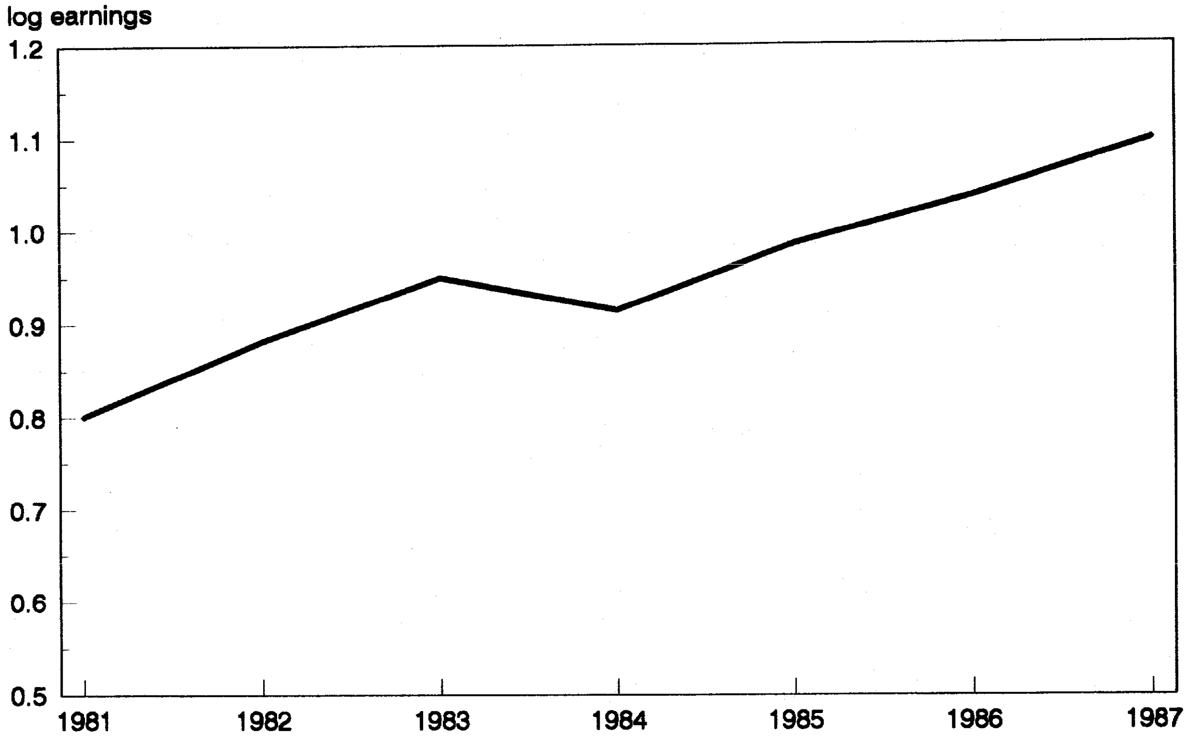


Figure 10: Returns to college
Medium-sized and large firms

(a) Average



(b) By industries

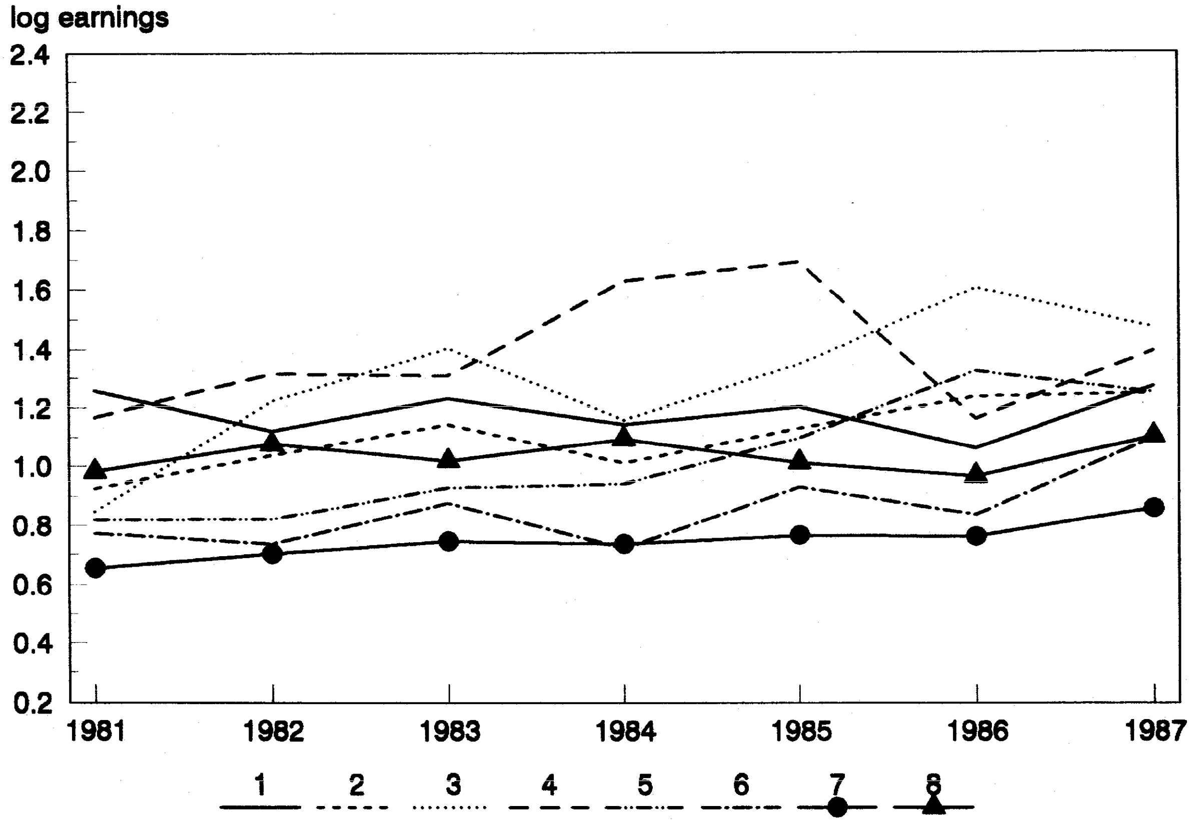


Figure 11: Returns to junior college
Small firms

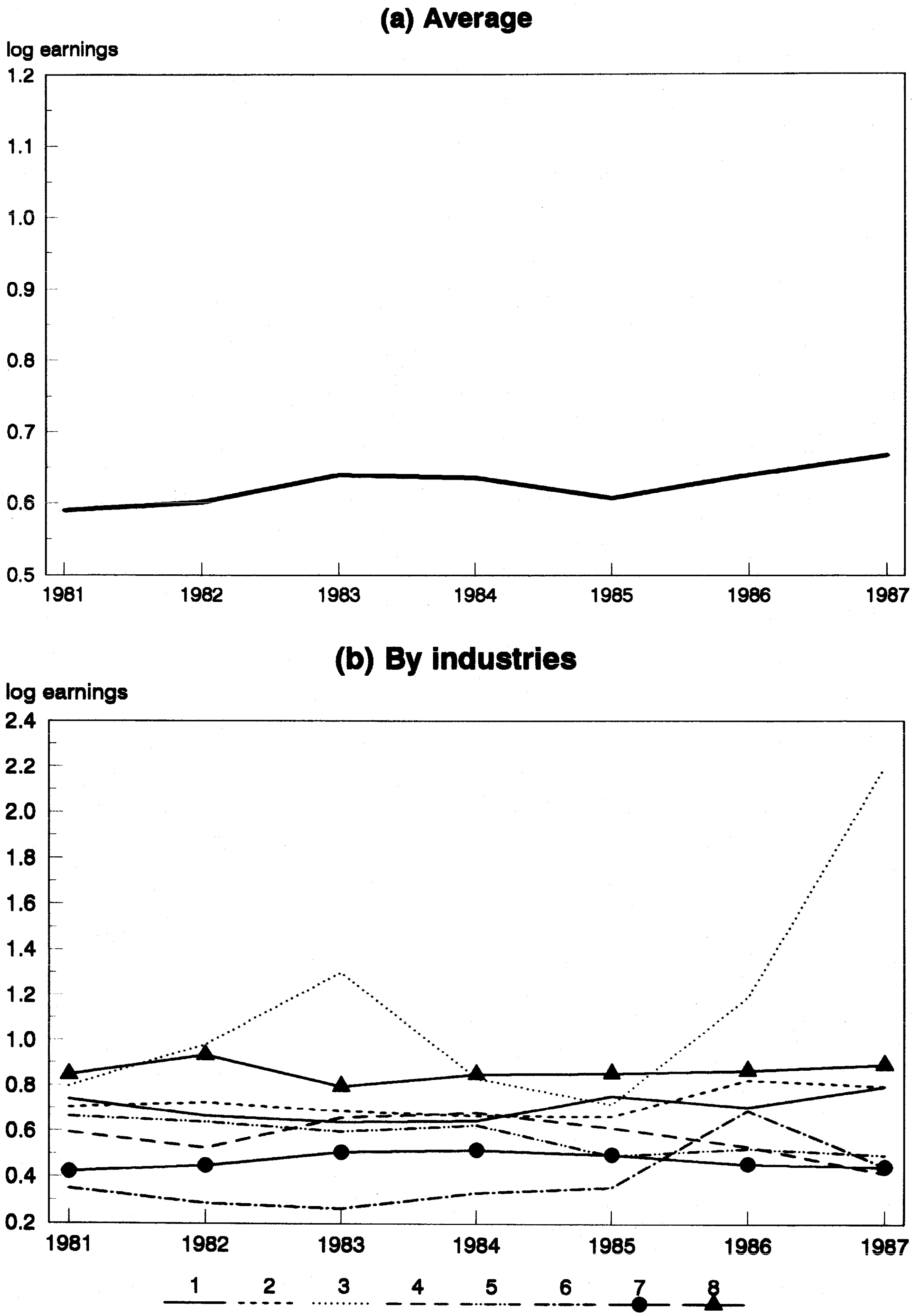
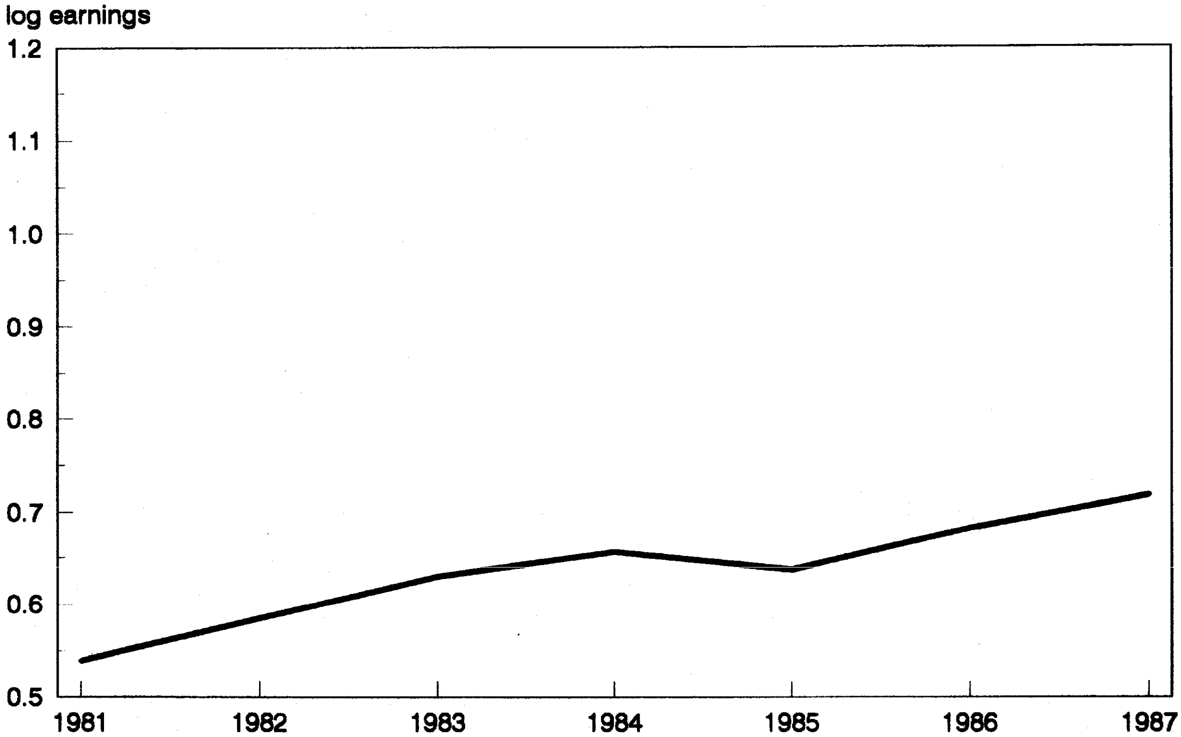


Figure 12: Returns to junior college
Medium-sized and large firms

(a) Average



(b) By industries

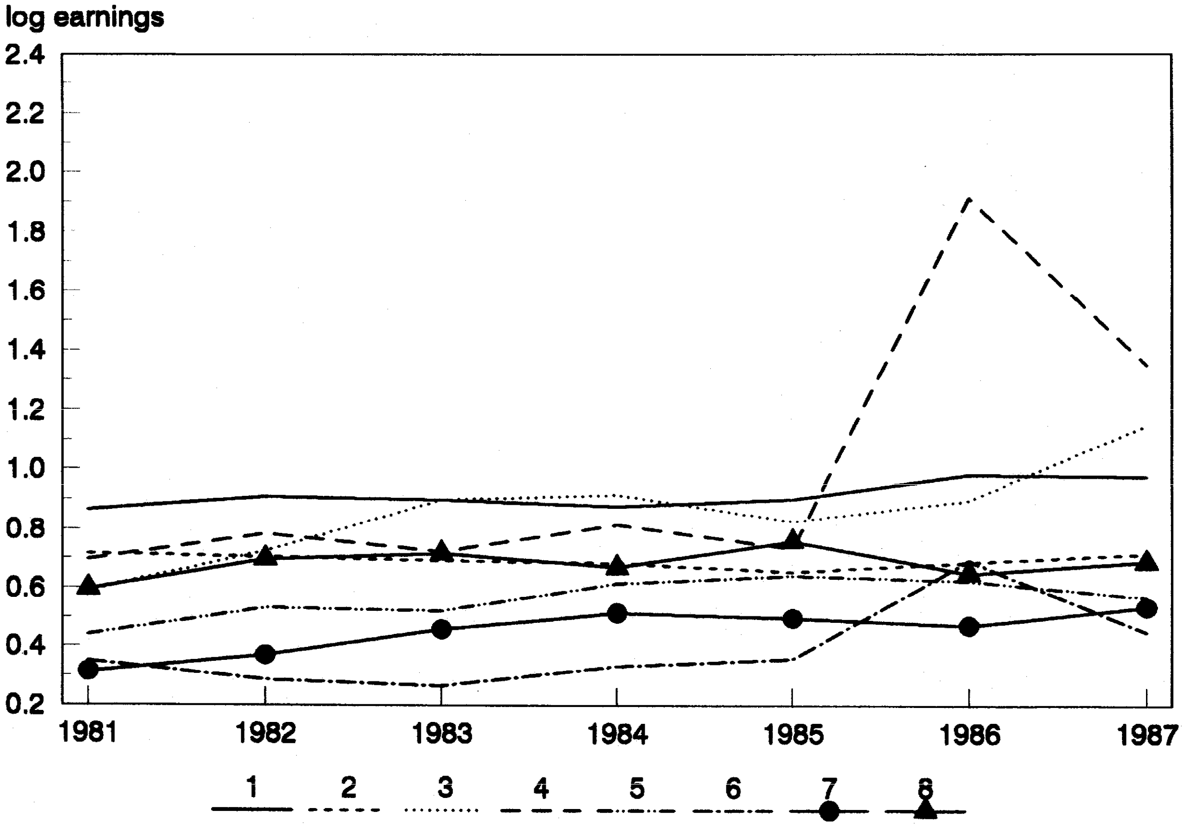
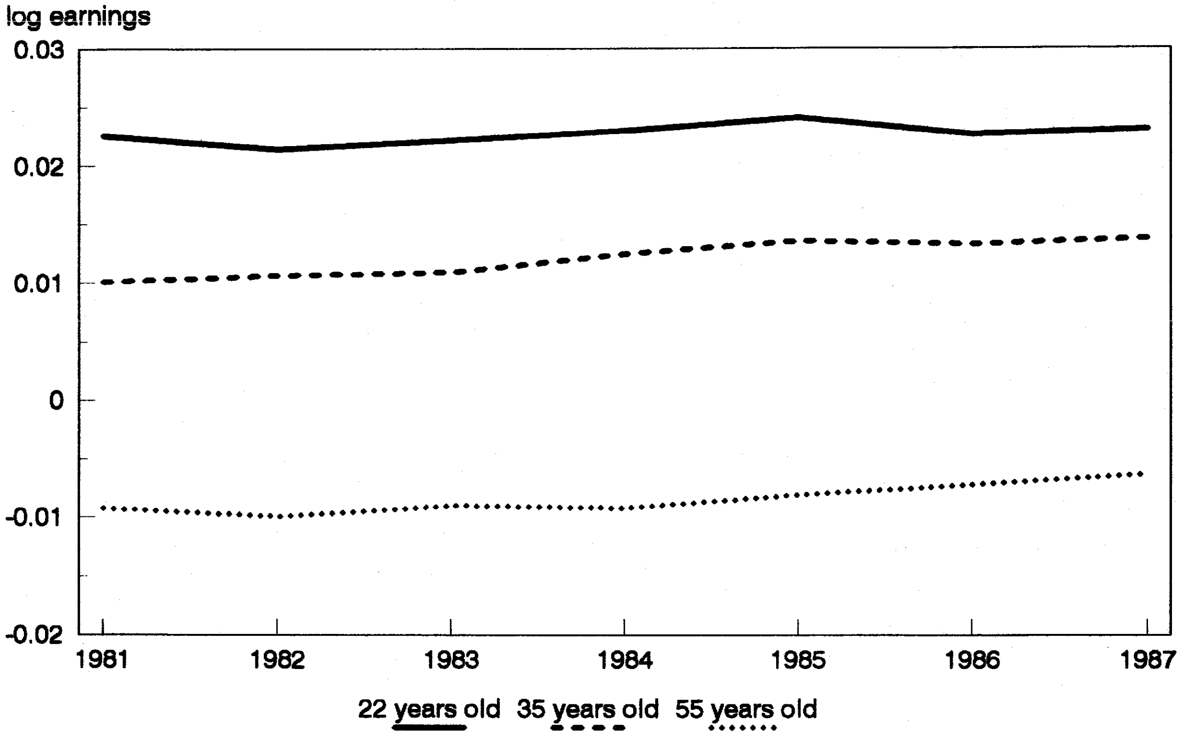
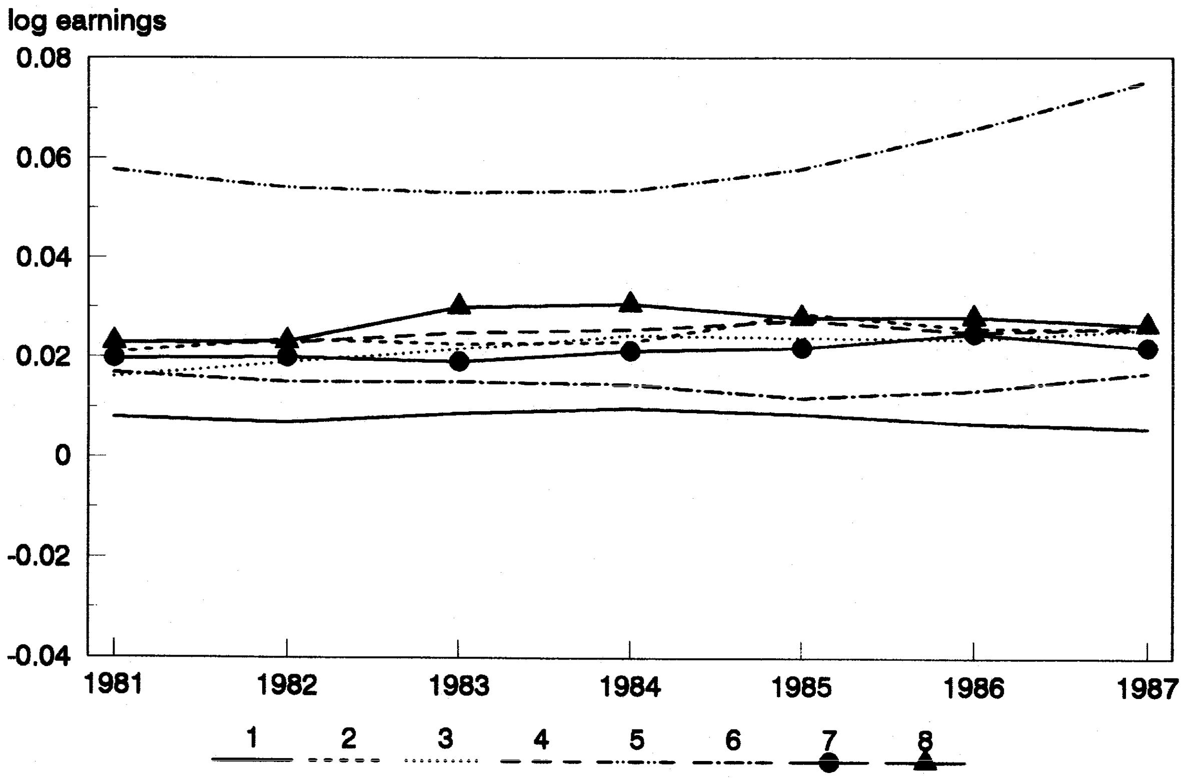


Figure 13: Returns to age

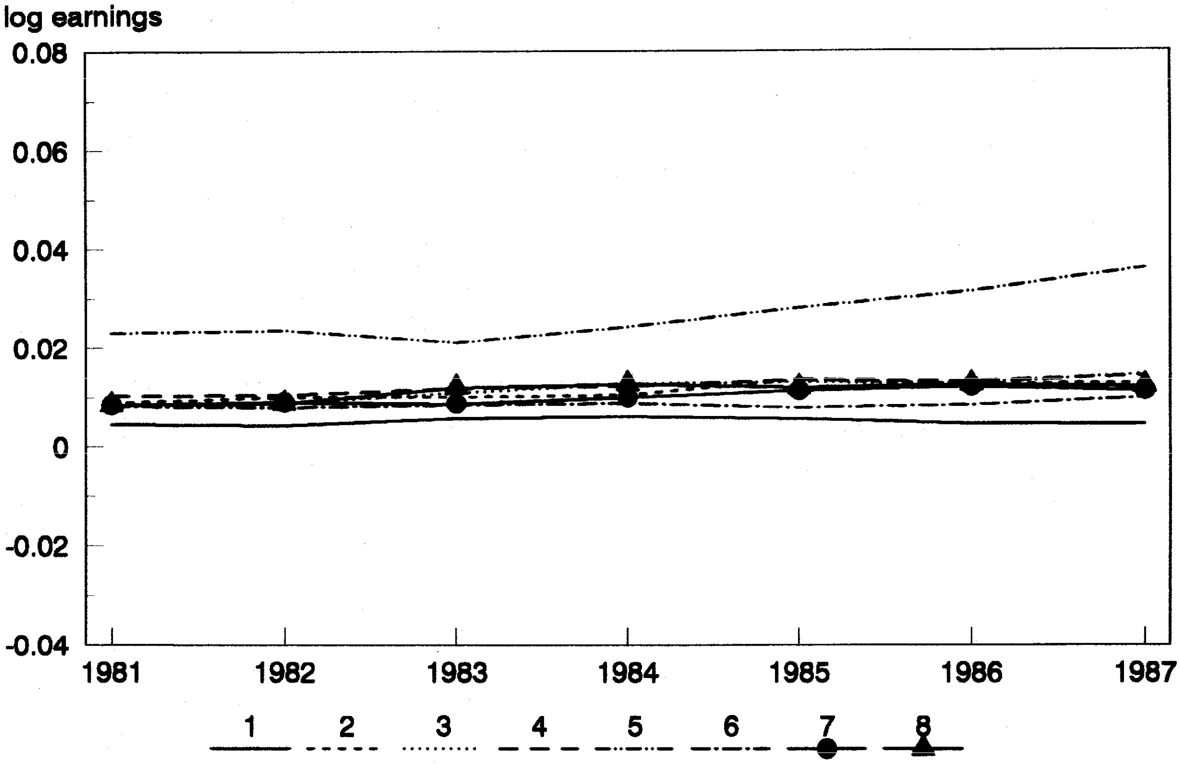
(a) Average



(b) By sectors
22 years old



(c) By sectors
35 years old



(d) By sectors
55 years old

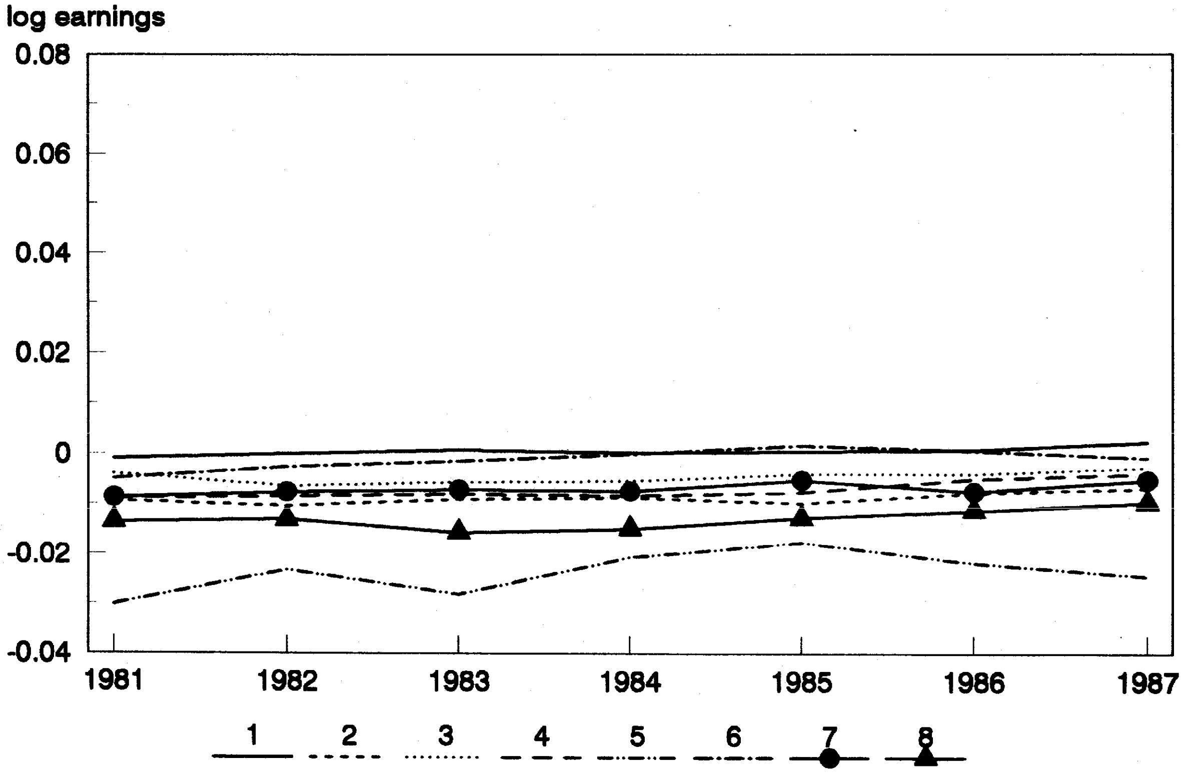


Figure 14: Effect of firm size on the conditional log-variance, by skill group

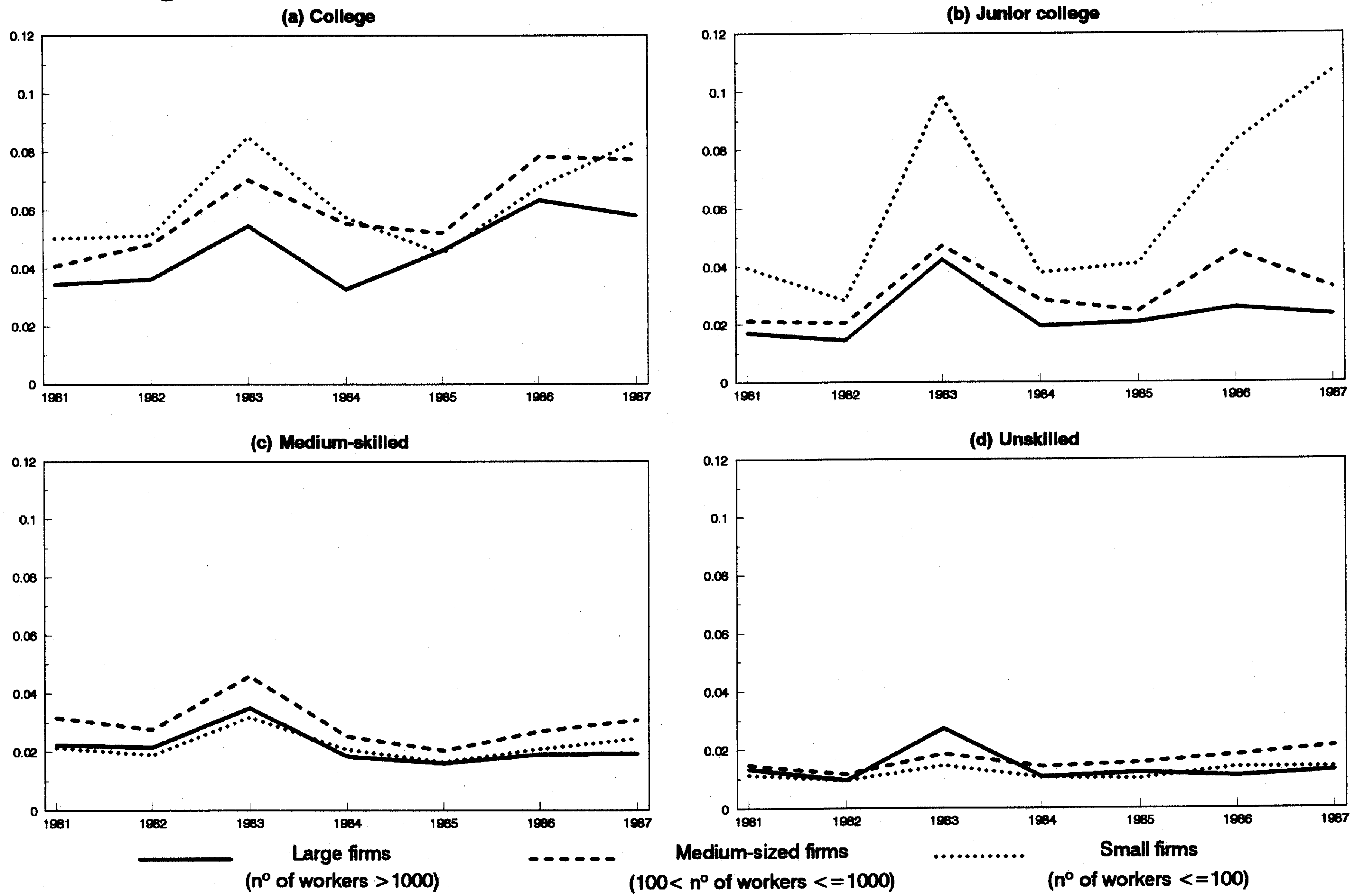


Figure 15: Effect of college education on the conditional log-variance

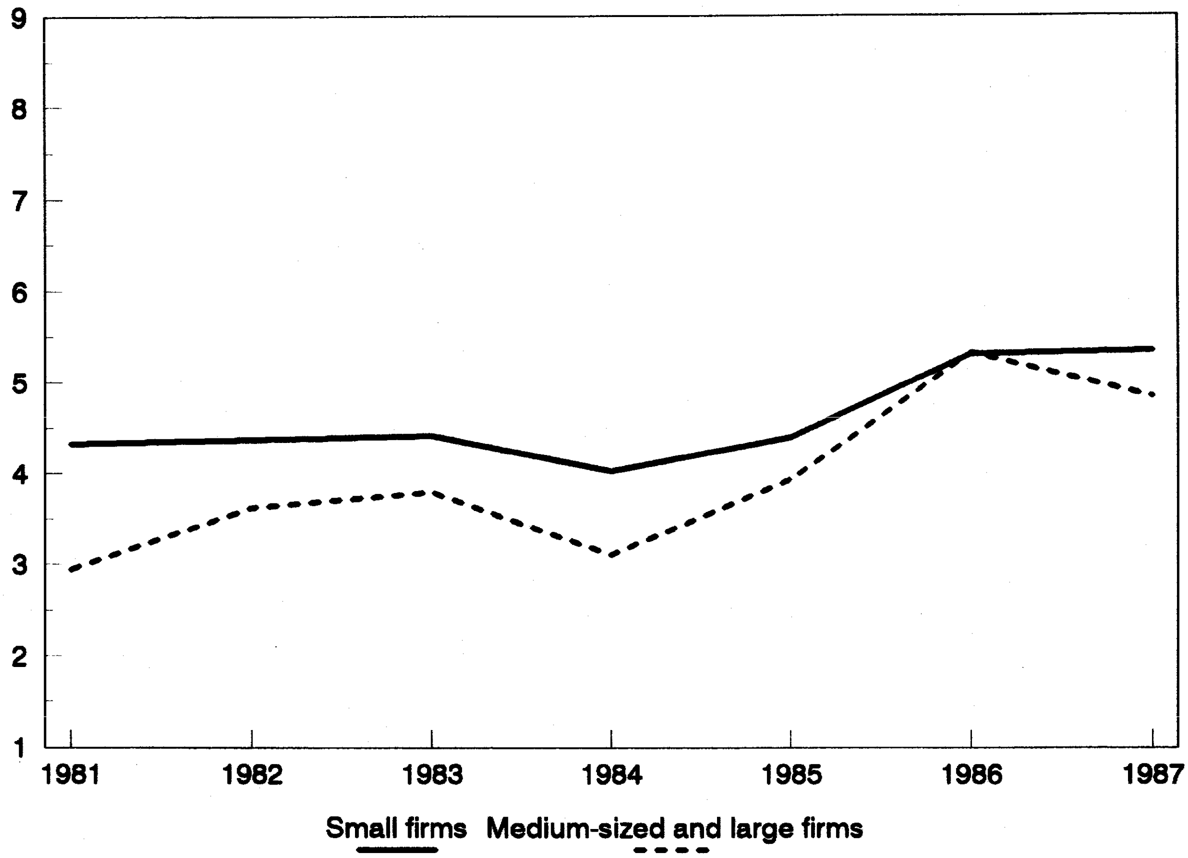
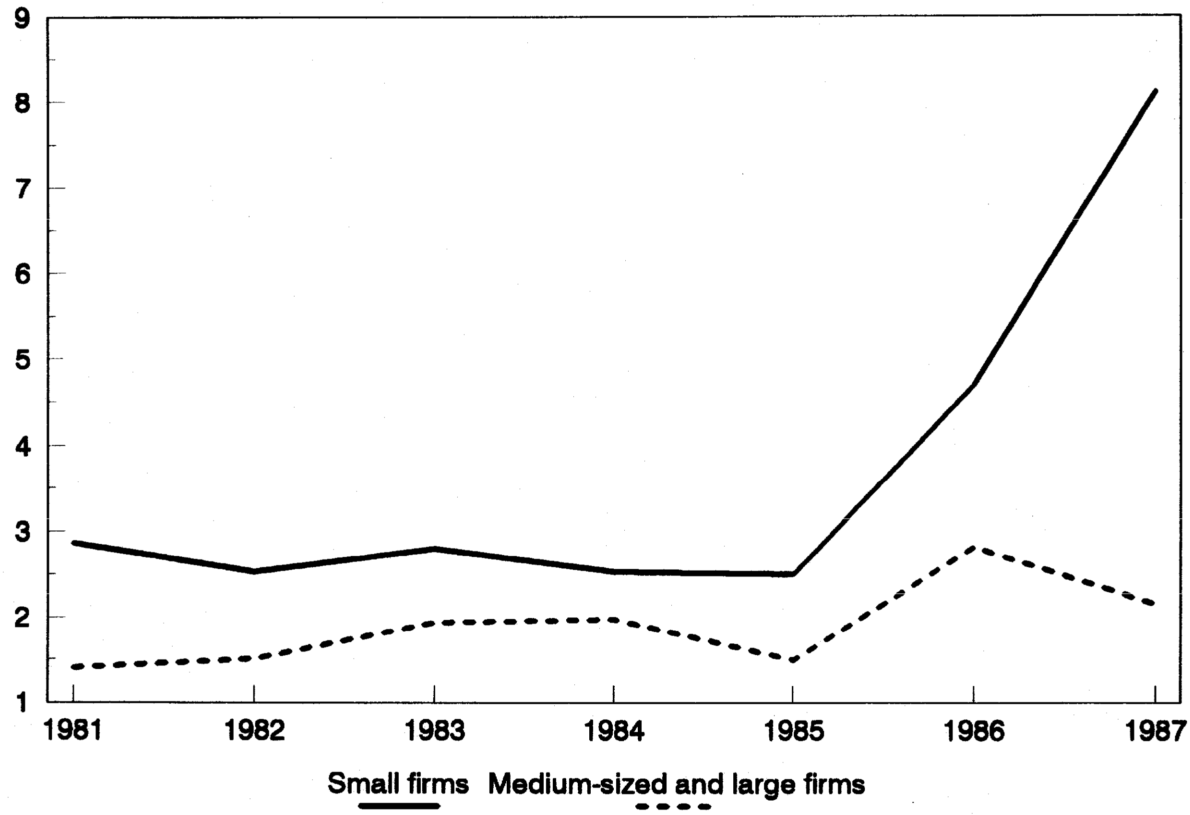


Figure 16: Effect of junior college education on the conditional log-variance

(a) Average



(b) Excluding transport and public utilities

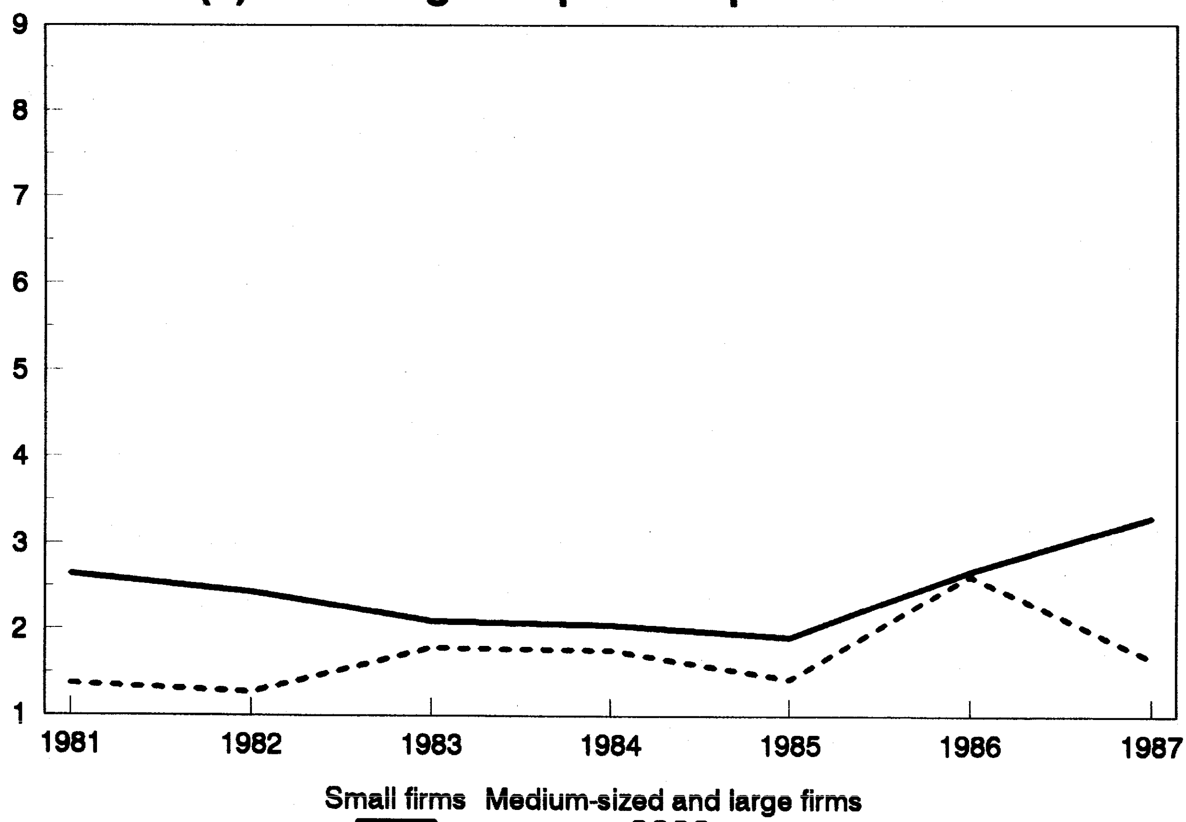


Figure 17: Effect of age on the conditional log-variance