Does part-time schooling pay? Panel quantile-regression evidence

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ABSTRACT

This paper assesses whether part-time schooling pays by estimating the conditional quantile wage returns to both part-time and full-time schooling. Exploring longitudinal data on Portuguese male workers from the European Community Household Panel (ECHP, 1994-2000), we find that part-time schooling is dominated by full-time schooling.

KEYWORDS: working students, return to schooling, wage level, panel data.
JEL Classification: I21, J31, C23.

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Acknowledgments
The authors gratefully acknowledge financial support from the European Commission (EDWIN Project, HPSE-CT-2002-00108) and from the Fundação para a Ciência e a Tecnologia (CEEAplA funding). For useful comments on earlier versions of this manuscript, the authors would like to thank the participants at the 1st Annual Meeting of the Portuguese Economic Journal, the 23rd National Conference of the Italian Association of Labour Economists (AIEL), the 20th Conference of the European Association of Labour Economists (EALE) and the 21st Meeting of the Spanish Economics of Education Association (AEDE). Part of this paper has been written while Corrado Andini was visiting the Economic Research Department at the Banco de Portugal. The usual disclaimer applies.

1. Introduction

The seminal book by Jacob Mincer (1974) on *Schooling, Experience and Earnings* is the starting point of a large body of literature dealing with the estimation of a linear model where the logarithm of the hourly wage of an individual is explained by schooling years, labour-market experience and experience squared.

The Mincerian framework is a corner-stone of modern education economics, although it has some limitations. One of the limitations of the framework is the hypothesis that individuals start working after leaving school, which is quite not the case for many people in many countries. Indeed, as stressed by Light (2001, p. 65), “students often accumulate substantial work experience before leaving school”.

A 2006 report summarizing the experiences of eight European countries in 2000 shows that the ratio of working students to total students varies from 48 percent in France to 77 percent in the Netherlands (see Häkkinen, 2006). Despite the numerical relevance of working students, the first attempt to control for in-school work experience when estimating the Mincerian return to schooling is relatively recent. In particular, using data from the US National Longitudinal Survey of Youth, Light (2001) found that disregarding in-school work experience implies a substantial overestimation of the schooling return.

Of course, the above-referred study by Audrey Light is neither the only nor the first study in the literature on wages and in-school work. On the contrary, this research field is relatively rich in contributions. From a theoretical point of view, the debate on the benefits and costs of in-school work presents two clear and opposite views. On the one hand, there are those who maintain that working while enrolled in school is positive because it fosters the development of personal responsibility and good work-habits. On the other hand, there are those who criticize this practice because it interferes with learning activities at school, delaying schooling achievements (see Schoenhals et al., 1998 for a review).

As for the theory, the empirical evidence accumulated in the field so far is also mixed. Many authors find evidence in favour of in-school work in terms of substantial higher wages later in life. However, an important study by Hotz et al. (2002) questions this whole body of evidence because sample selection is not controlled for. Indeed, the authors find that controlling for selection completely eliminates the positive impact of in-school work on future earnings.

Another striking feature of the existing empirical literature is that it is almost exclusively related to the case of the United States. A 2006 article by Häkkinen (2006) is one of the first attempts to fill the gap between the European Union and the United States. The author asks whether it pays to work while enrolled in school in Finland, with results that are in line with those proposed by Hotz et al. (2002).

Summarizing, the most recent literature suggests that the conditional average wage return to one year of in-school work is either very low or completely absent. This suggests that part-time schooling has little impact on the mean of the conditional wage distribution. In particular, it raises the question of whether it is worth spending one year of life as a part-time student rather than as a full-time student. Since the conditional mean wage return to one year of full-time schooling is typically found to be above 5%, part-time schooling does not seem to be a valuable choice. However, to make a more definitive statement, we believe that some piece of information is still needed. Let us explain why.

A standard view in finance is that individuals do not care only about the expected return of an investment. They also care about the risk. This is also relevant for the schooling investment and, in particular, for the choice between part-time and full-time schooling. For instance, by choosing full-time schooling, an individual may end up in a conditional wage distribution characterized by higher mean but also higher dispersion. In contrast, by choosing part-time schooling, an individual may end up in a conditional wage distribution characterized by lower mean but also lower dispersion. That is, there may be a trade-off between mean and dispersion that the literature has not explored yet.

As it stands now, there seem to be a number of open questions in the literature: Is the impact of part-time schooling on the mean of the conditional wage distribution really low? Is it lower than the impact of full-time schooling? What is the impact of part-time schooling on the dispersion of the conditional wage distribution? Is it lower than that of full-time schooling? The answers to these questions seem crucial.

This paper attempts to shed new light on the mechanics of the return-risk link in education and contributes to the ongoing debate (among others, see Levhari and Weiss, 1974; Pereira and Martins, 2002; Harmon et al., 2003; Hartog et al., 2004; Cunha et al., 2005; Christiansen et al., 2007; Hartog and Vijverberg, 2007; Hogan and Walker, 2007; Andini, 2009). In particular, we are interested in the question of whether being a part-time student actually pays. To provide new insights, we propose a novel methodology based on conditional quantile wage returns.

As we will see, the answer is complex. Considering mean estimates only, we answer 'no'. Therefore, our answer is in line with the findings by both Hotz et al. (2002) and Häkkinen (2006). However, considering dispersion estimates only, we answer 'yes'. Therefore, considering both mean and dispersion estimates, the answer to our main research question may appear controversial. However, it is not. Indeed, after measuring the wage returns to both full-time schooling and part-time schooling along quantiles of the conditional wage distribution, we find that the lowest return to full-time schooling is higher than the highest return to part-time schooling. Thus, the full-time schooling strategy dominates the part-time schooling strategy, providing an economic reason for ultimately answering 'no' to our main research question.

The evidence is based on Portuguese data from the European Community Household Panel (ECHP, 1994-2001). We provide causal estimates. Yet, our estimates are based on the assumptions that individual unobserved heterogeneity is uncorrelated with the observables and that selection is based on observables and time-invariant orthogonal unobservables. Since we are aware that these are crucial assumptions, we support them by presenting the results of specification tests. The standard practice in wage-schooling models is to use instrumental variables and/or selection equations to deal with undesired correlations. Sometimes, this is done without testing whether undesired correlations are actually in place. Due to the current emphasis on quasi-natural experiments, it has become more frequent to read articles based on assumptions that cannot be tested, such as exclusion restrictions, than articles based on testable assumptions. This paper reminds that assumption testing is important and a well-specified model can make life easier. The novelty, to the best of our knowledge, is that we provide conditional quantile estimates of the wage returns to different schooling strategies, using panel data. In addition, our return estimates are comparable to each other, thus allowing for an analysis of dominance between schooling strategies.

The paper is organized as follows. Section 2 discusses data and empirical approach. Section 3 presents the estimation results. Section 4 concludes.

2. Empirical approach

This section discusses our empirical approach with particular focus on the economic meaning of the estimates, regression model, construction of variables and data, and econometric problems. Specific estimation issues will also be discussed in the next section.

2.1 Economic meaning of the estimates

Let W and S be the individual log-wage and the individual schooling years, respectively. To be precise about what we are going to estimate, let us consider the following simple wage model $W = \alpha + \beta S + \xi$ under the assumptions that $E(\xi|S) = 0$ and $Q_\theta(\xi|S) = 0$ for each θ. The latter is a given quantile of the conditional wage distribution.

Under the above assumptions, the mean of the log-wage distribution conditional on S years of schooling is given by $E(W|S) = \alpha + \beta S$, while the mean of the log-wage distribution conditional on $S+1$ years of schooling is given by $E(W|S+1) = \alpha + \beta(S+1)$.

Analogously, the θ^{th} quantile of the log-wage distribution conditional on S years of schooling is given by $Q_\theta(W|S) = \alpha_\theta + \beta_\theta S$, while the θ^{th} quantile of the log-wage distribution conditional on $S+1$ years of schooling is given by $Q_\theta(W|S+1) = \alpha_\theta + \beta_\theta(S+1)$.

Hence, a measure of the dispersion of the log-wage distribution conditional on S years of schooling is given by $Q_{90}(W|S) - Q_{10}(W|S)$, while a measure of the dispersion of the log-wage distribution conditional on $S+1$ years of schooling is given by $Q_{90}(W|S+1) - Q_{10}(W|S+1)$.

It follows that an increase (decrease) in the dispersion of the conditional log-wage distribution when schooling years increase by one year can be measured by the difference $[Q_{90}(W|S+1) - Q_{10}(W|S+1)] - [Q_{90}(W|S) - Q_{10}(W|S)]$.

Under the above hypotheses, it is easy to show that the β coefficient estimated by ordinary least squares (OLS) measures the increase (decrease) in the mean of the conditional log-wage distribution when schooling years increase by one year, i.e. $\beta^{OLS} = E(W|S+1) - E(W|S)$.

In addition, the β_θ coefficient estimated by using the quantile-regression (QR) estimator by Koenker and Bussett (1978) measures the increase (decrease) in the θ^{th} quantile of the conditional log-wage distribution when schooling years increase by one year, i.e. $\beta_\theta^{QR} = Q_\theta(W|S+1) - Q_\theta(W|S)$.

It follows that $\beta_{90}^{QR} - \beta_{10}^{QR} = [Q_{90}(W|S+1) - Q_{90}(W|S)] - [Q_{10}(W|S+1) - Q_{10}(W|S)]$ is identically equal to $[Q_{90}(W|S+1) - Q_{10}(W|S+1)] - [Q_{90}(W|S) - Q_{10}(W|S)]$. Hence, the difference

$\beta_{90}^{QR} - \beta_{10}^{QR}$ can be used to measure the increase (decrease) in the dispersion of the conditional log-wage distribution when schooling years increase by one year.

In short, β^{OLS} measures the increase (decrease) in the mean of the conditional log-wage distribution when schooling years increase by one year, while $\beta_{90}^{QR} - \beta_{10}^{QR}$ measures the increase (decrease) in the dispersion of the conditional log-wage distribution when schooling years increase by one year. Alternatively, the former measures the impact of schooling on the conditional wage mean, i.e. the conditional average wage return. The latter measures the impact of schooling on the conditional wage dispersion.

If one considers more complex estimators (for instance, those taking into account individual specific effects) rather than simple OLS and QR, the economic meaning of the estimates does not change.

2.2 Regression model

Using individual-level panel data, the original Mincerian model suggests the estimation of the following wage equation:

$$(1) \quad W_{it} = \beta_0 + \beta_1 S_i + \beta_2 Z_{it} + \beta_3 Z_{it}^2 + \beta_i + \beta_t + \xi_{it}$$

where W represents the natural logarithm of the individual gross hourly wage, S represents full-time schooling years, $Z = AGE - S - 6$ stands for potential full-time labour-market experience (AGE is individual age), β_i and β_t are vectors containing individual and year effects respectively, and ξ is an orthogonal error term.

For the purpose of this paper, we suggest one simple departure from the above empirical setting. In particular, we distinguish between years of full-time schooling, labelled as S_1, and years of part-time schooling, labelled as S_2. In addition, we allow for different returns.

In summary, we estimate the following empirical model:

$$(2) \quad W_{it} = \beta_0 + \beta_1 S_{1i} + \beta_2 S_{2i} + \beta_3 Z_{it} + \beta_4 Z_{it}^2 + \beta_i + \beta_t + \xi_{it}$$

Besides all time-invariant individual characteristics and year effects, we control for a set of observed time-varying individual characteristics. In particular, our control set includes information on occupation[1], job status (supervisor or not), health status (very good, good, fair, bad, very bad), industry (agriculture, manufacturing, services), migration status (immigrant or not), sector of activity (public or private) and marital status (married, separated, divorced, widowed, never married).

2.3 Data and variables

Concerning the data, we use all the available waves of the European Community Household Panel (ECHP) from 1994 to 2001. Specifically, we focus on a perfectly balanced sample of 493 full-time Portuguese male workers, aged between 18 and 65, former working students. We focus on males to minimize sample-selection problems typically arising with females. The main variables in the sample are described in Table 1.

[1] The occupation categories are nine: 1) legislators, senior officials and managers; 2) professionals; 3) technicians and associate professionals; 4) clerks; 5) service workers and shop and market sales workers; 6) skilled agricultural and fishery workers; 7) craft and related trades workers; 8) plant and machine operators and assemblers; 9) elementary occupations.

(Insert Table 1)

The variable W, the natural logarithm of the individual gross hourly wage, is measured as usual in the literature. From the gross monthly wage, we obtain the weekly wage. Dividing the latter by the number of weekly hours of work, we obtain the hourly wage.

Instead, the remaining variables require some additional comments. In particular, since the main criticism to in-school work is the argument that working while enrolled in school may delay education achievements, in order to properly account for the effect of part-time schooling on wages, it is important to measure part-time schooling years by taking this criticism into account. In practice, one has to take into account that individuals may not successfully complete some schooling years during their studies because of their in-school work and, as a consequence, their education level may not be a good indicator of their number of schooling years, particularly in the case of part-time schooling.

Unfortunately, the ECHP dataset neither contains information on part-time schooling years nor on total schooling years. It only provides information of individual education levels. Hence, one needs to infer part-time schooling years indirectly. The way we deal with this important issue is as follows. In order to obtain values for S_1, S_2 and Z, we use the following three ECHP questions:

PT023) Individual age at the completion of the highest level of general or higher education

PE039) Individual age at the start of the working life (first job or business)

PD003) Individual age

To begin with, we select a sample of Portuguese male workers such that $PT023 > PE039$, i.e. we restrict our sample to individuals who have potentially been working students at least for one year in their lives. Then, we define the above-referred variables as follows:

Potential total schooling years

$$S = PT023 - 6$$

Potential part-time schooling years (or potential part-time labour-market experience)

$$S_2 = PT023 - PE039$$

Potential full-time schooling years

$$S_1 = S - S_2 = (PT023 - 6) - (PE023 - PE039) = PE039 - 6$$

Potential full-time labour-market experience

$$Z = AGE - S - 6 = PD003 - (PT023 - 6) - 6 = PD003 - PT023$$

Finally, we remove from the sample individuals with time-varying schooling years (it happens, in few cases in our dataset, when an individual reaches a higher education level in the time-frame between two interviews).

The sample descriptive statistics in Table 1 report that Portuguese male workers, former working students, have on average 8.5 years of potential full-time schooling and 2.5 years of potential part-time schooling. These numbers compare favourably with the dataset information about education levels. Yet, there are three things that should be stressed. First, these numbers do not necessarily reflect actual schooling years. Indeed, they measure potential schooling years. Second, these numbers do not necessarily reflect successfully completed years of schooling. This is an interesting point for the reasons explained above. Third, the years of potential part-time schooling are, at the same time, years of potential part-time labour-market experience. It could not have been otherwise if one only suggests a unique deviation from the original Mincerian approach, as we do.

Of course, our approach has some limitations. As a matter of fact, the available information in the ECHP dataset does not allow us to follow a different strategy. However, we will discuss problems related to potential measurement errors in the schooling variables in the next section.

2.4 Measurement errors, ability, and selection

There are three types of issues that may bias the random-effects (RE) estimation of the schooling coefficients in model (2): i) correlation of the individual specific effects with the schooling variables due to measurement errors; ii) correlation of the individual specific effects with the schooling variables due to unobserved abilities; iii) correlation between the unobservable factors affecting the wage level and those affecting the decision to be a part-time student, i.e. non-random selection of the sample.

We will discuss each of these issues in what follows. Let us start with measurement errors. For simplicity, let us disregard experience and time effects in model (2) as well as the control set described before. Suppose the true model is $W_{it} = \alpha + \beta_1 S_{1i}^a + \beta_2 S_{2i}^a + \xi_{it}$ where S_{1i}^a measures the actual full-time schooling years of an individual and S_{2i}^a measures the actual part-time schooling years of the same individual. Yet, suppose the actual schooling years are measured with errors, such that $S_{1i} = S_{1i}^a + u_{1i}$ where S_{1i} measures the observed full-time schooling years, corresponding to the potential full-time schooling years in our dataset, and u_{1i} is the measurement error. Suppose the same happens with part-time schooling, so that we have $S_{2i} = S_{2i}^a + u_{2i}$. Thus, the wage model becomes $W_{it} = \alpha + \beta_1 S_{1i} + \beta_2 S_{2i} - \beta_1 u_{1i} - \beta_2 u_{2i} + \xi_{it}$. In this case, if the vector $-\beta_1 u_{1i} - \beta_2 u_{2i}$ is orthogonal to S_{1i} and S_{2i}, then β_1 and β_2 are consistently and efficiently estimated using the RE estimator. The hypothesis of orthogonality can be tested by comparing fixed-effects (FE) and random-effects estimates through the Hausman test. If the null is not rejected, then orthogonality can be reasonably assumed.

Let us now consider abilities. Suppose the wage model also includes a vector of individual unobserved abilities, say A_i. Thus, it becomes $W_{it} = \alpha + \beta_1 S_{1i} + \beta_2 S_{2i} - \beta_1 u_{1i} - \beta_2 u_{2i} + \gamma A_i + \xi_{it}$. Even in this case, if the vector $-\beta_1 u_{1i} - \beta_2 u_{2i} + \gamma A_i$ is orthogonal to the schooling variables, then the coefficients of the schooling variables are consistently and efficiently estimated using the RE estimator. Again, we can test this hypothesis using the Hausman test.

Finally, let us consider the sample-selection issue. Some of the unobservable factors that affect the wage level (the unobserved residuals ξ_{it}) may be correlated with some of the unobservable factors affecting the decision to be a part-time student. In this case, the RE estimates of the schooling coefficients would be biased. Yet, we can simply test this hypothesis by following the procedure suggested by Nijman and Verbeek (1992). If selection is not ignorable, then the choice variable D_{it-1}, which is equal to one (zero) if the individual has (not) chosen to be in part-time schooling at time $t-1$, is statistically significant in the RE model $W_{it} = \alpha + \beta_1 S_{1i} + \beta_2 S_{2i} - \beta_1 u_{1i} - \beta_2 u_{2i} + \gamma A_i + \delta D_{it-1} + \xi_{it}$. Should this binary variable not be significant, then the coefficients of the schooling variables are consistently and efficiently estimated using the RE estimator.

Since our dataset has a longitudinal structure and the RE estimator explicitly controls for the vector $\beta_i = -\beta_1 u_{1i} - \beta_2 u_{2i} + \gamma A_i$ under the testable hypothesis that this vector is orthogonal to the explanatory variables, the first step is to test whether orthogonality can be assumed. The second is to apply the Nijman-Verbeek procedure to test whether selection matters. This is what we do in the next section.

3. Estimation results

This section presents the estimation results. It is divided in four sub-sections. The first provides the results of specification tests. The second focuses on the conditional average wage returns. The third presents estimates of the conditional quantile wage returns. The fourth focuses on the dominance issue referred in Section 1.

3.1. Specification tests

The Hausman test comparing FE and RE estimates of model (2) does not reject the null hypothesis (p-value 0.189). Thus, the vector $\beta_i = -\beta_1 u_{1i} - \beta_2 u_{2i} + \gamma A_i$ can be assumed to be orthogonal to the explanatory variables. Hence, the potential biases induced by measurement errors and abilities in the schooling variables do not seem to be an issue in this paper.

An intuition for the above result is that individual abilities may be positively correlated with schooling variables while measurement errors may be negatively correlated. Thus, the correlation of the whole vector with the schooling variables might be close to zero. It follows that the RE estimator is a consistent and efficient estimator of model (2), unless selection bias matters.

To construct the part-time schooling choice dummy, we use the whole available sample of 901 Portuguese male workers (7208 rather than 3944 obs.), aged between 18 and 65, which includes individuals who have never been part-time students. Then, using this sample, we generate an indicator-variable for the part-time schooling choice. Specifically, we find that the coefficient of the lagged value of the part-time schooling choice variable is close to zero (0.018) and it is not statistically significant (p-value 0.167).

An intuition for the above result is that the individuals in our sample self-select into part-time schooling based on variables that we control for in the wage equation. Thus, controlling for individual time-invariant effects and a set of other characteristics in the wage equation seem to be enough to break any correlation between the residuals of the wage equation and those of the equation modelling the part-time schooling choice.

In short, the RE estimates of the schooling coefficients seem to be reliable. Of course, claiming causality in a wage-schooling model is always a difficult task, and we are aware that the above results for both the Hausman test and the Nijman-Verbeek test are likely to be specific to our sample.

In addition, it should be noted that the only instrumental variable potentially available in the ECHP dataset for the identification of a wage-schooling model is the quarter of birth, which can be inferred from the information on the individual month of birth. Yet, the validity of the use of the quarter of birth as an instrument has been questioned in two important studies: one authored by Bound et al. (1995) and another one, more recent, due to Buckles and Hungerman (2013). In particular, Buckles and Hungerman (2013) suggest that the exclusion restriction is likely to be violated. In sum, the problem of the identification of wage-schooling models through the season of birth is still open, but an assessment of the technicalities involved in the debate goes beyond the aim of this paper.

Finally, one additional argument supporting the approach we take in this paper is that our main conclusion is based on an analysis of dominance. The latter, as shall be discussed later, takes into account the difference between the coefficient of full-time schooling at the lowest decile of the conditional wage distribution and the coefficient of part-time schooling at the highest decile. Hence, even if the schooling coefficient estimates are biased for some reason, there is no strong reason to believe that they are biased in different directions or different magnitudes. The consequence is that the difference between them might be bias-free because the respective biases cancel out.

3.2 Conditional average wage returns

Although our preferred estimates are the RE estimates, we also provide OLS estimates of model (2) as benchmark. In particular, the OLS estimates presented in Table 2 suggest that the conditional average wage return to full-time schooling is higher than the corresponding return to part-time schooling. A formal test also confirms that the two coefficients are statistically different. The magnitude of this difference is around 7 percent points (OLS: 0.089 vs. 0.019).

(Insert Table 2)

If we allow for the existence of individual specific intercepts, the qualitative results do not change. Indeed, the RE estimator confirms the significant spread between the full-time schooling average return and the part-time schooling one (RE: 0.105 vs. 0.027). The former is almost four times bigger than the latter. However, the estimated coefficients are not similar, and the Hausman test between OLS and RE estimates rejects the null (p-value 0.031). This is an indirect indication that the variance of the individual specific effects is larger than zero. More importantly, it supports the view that a model with individual specific intercepts is needed.

3.3 Conditional quantile wage returns

The quantile-regression approach originally proposed by Koenker and Bassett (1978) is nowadays very popular in applied economics. It allows us to characterize the effect of a covariate along quantiles of the conditional distribution of the dependent variable. This is interesting because a result for the conditional mean may be driven by something happening at specific quantiles.

A few years ago, the advantages of quantile regression has been combined with those of panel data. Indeed, Koenker (2004) has introduced an estimator for quantile-regression models with fixed effects conceived as pure location shifters. His approach involves the exogenous choice of a penality parameter. However, building on Koenker's (2004) original article, in an important contribution, Lamarche (2010) has proposed a method to endogenously choose the penality parameter under the additional assumption that fixed effects and covariates are independent.

In order to obtain conditional quantile estimates comparable with our conditional mean estimates, it is important to use not only the same sample and model specification but also a quantile-regression estimator that is conceptually close to our preferred RE (mean) estimator. Such estimator is clearly the one proposed by Lamarche (2010). Indeed, Lamarche's estimator explicitly assumes that the individual specific effects are orthogonal to the explanatory variables.

So, using Lamarche's approach, we will estimate the following model:

$$\text{(3)} \quad W_{it} = \beta_0 + \beta_{1\theta} S_{1i} + \beta_{2\theta} S_{2i} + \beta_{3\theta} Z_{it} + \beta_{4\theta} Z_{it}^2 + \beta_i + \beta_{t\theta} + \xi_{it\theta}$$

where θ represents a given quantile of the conditional wage distribution and β_i is a vector of individual specific effects, assumed to orthogonal to the model covariates and independent of the quantile θ. We label the estimates of $\beta_{1\theta}$ and $\beta_{2\theta}$ as random-effects-quantile-regression (REQR) estimates. However, for sake of comparison, we also provide simple quantile-regression estimates (QR), which disregard individual specific effects.

Table 3 presents both QR and REQR estimates. The main finding is that the coefficient estimates increase along quantiles of the conditional wage distribution (from Q10 to Q90). This means that both part-time schooling and full-time schooling have positive impacts on the dispersion of the conditional wage distribution.

(Insert Table 3)

Following Pereira and Martins (2002), we measure the impacts on the conditional wage dispersion as differences between the wage return at the ninth decile (Q90) and that at the first decile (Q10), using the estimates in Table 3. Table 4 presents the results. In particular, the last column of Table 4 focuses on our preferred REQR estimates. The key result is that the increase in the conditional wage dispersion implied by full-time education is much bigger than the one implied by part-time education (REQR: 0.047 vs. 0.013), meaning that there is clear evidence of a trade-off between mean and dispersion impacts.

The above qualitative result also holds when a simple quantile-regression estimator is used (QR: 0.066 vs. 0.022). However, as one may reasonably expect, controlling for individual specific intercepts reduces the impact of each type of schooling attendance on residual wage inequality (if one could control for everything, then, in the limit, residual wage inequality should be zero). The penality parameter endogenously chosen by the Lamarche's estimator is around 0.9, thus further suggesting that shrinking individual effects towards a common value is rejected by the data.

(Insert Table 4)

3.4 Dominance

The existence of a trade-off may complicate policy considerations. Nevertheless, as shown in Table 3, based on REQR, the lowest return to full-time schooling is higher than the highest return to part-time schooling. The latter means that the full-time schooling strategy dominates the part-time schooling strategy. In addition, this dominance result is confirmed by simple QR.

4. Conclusions

This section briefly summarizes our main conclusions, also discussing the limitations of our analysis. Further, we present some policy considerations.

In this paper, we have first dealt with the estimation of conditional average wage returns to both part-time and full-time schooling, thus contributing to the existing body of empirical research on the conditional mean wage effects of in-school work. In particular, our results are in line with the previous findings by both Hotz et al. (2002) and Häkkinen (2006).

Then, in order to evaluate and compare the impacts of both full-time and part-time schooling on the conditional wage dispersion, we have provided estimates of conditional quantile wage returns. In particular, we have used a recently developed quantile-regression estimator for panel data due to Lamarche (2010). Hence, following a seminal article by Buchinsky (1994) for the United States, we have contributed to the existing research on within-groups wage inequality in Portugal (among others, see Machado and Mata, 2001; Hartog et al., 2001; Martins and Pereira, 2004; and Andini, 2008; Andini, 2010). In line with earlier studies using cross-sectional data for Portugal, we have found that both full-time and part-time schooling increase within-groups wage inequality.

To summarize, we have found that the strategy of studying and working at the same time pays, on average, less than the strategy of studying only. The magnitude of the difference is large and should not be disregarded by educational policy-makers in Portugal. The conditional mean earnings return to one additional year of full-time schooling is almost four times larger than that of part-time schooling. This suggests that the choice of working while enrolled in school is not worth because one year of full-time schooling provides at least the same average wage return as four years of part-time schooling.

If these results would imply the same impact on conditional wage dispersion, in an oversimplified conditional mean-variance world, then our policy recommendations would be relatively easy and twofold. First, universities should strongly limit the access of students to special curricula for working students. Second, public funds supporting the schooling activity of those who cannot finance their studies by themselves should be increased. This public investment would be repaid by higher average national earnings and tax receipts in the future.

However, our results do not imply the same underlying impacts on conditional wage dispersion, thus complicating policy considerations. Indeed, we have found that the impact of part-time schooling is much lower than that of full-time schooling, implying that that educational policies fostering full-time education in Portugal may significantly increase within-groups wage inequality in the future. Putting it differently, the existence of different impacts on conditional wage dispersion provides an economic reason for the existence of special curricula for working students, otherwise not justified by the empirical evidence on the conditional mean wage return to part-time schooling.

Nevertheless, since we have shown that full-time schooling dominates part-time schooling along the conditional wage distribution, the final answer to the main research question of this paper is not controversial. Does part-time schooling actually pay? We answer ‘no’. Yet, this answer should be taken with caution because it is exclusively based on conditional quantile wage returns and the causality argument is always a delicate issue in wage-schooling models. In addition, this paper does not measure other positive, even non-monetary, outcomes that can be obtained through part-time schooling or in-school work.

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Table 1. Summary sample statistics (main variables)

	Obs.	Mean	St. Dev.	Min	Max
W	3944	1.744	0.551	–0.0843	6.022
S_1	3944	8.592	3.193	4.000	16.000
S_2	3944	2.514	5.241	1.000	19.000
Z	3944	26.372	9.864	0.000	54.000

Notes: The whole summary sample statistics are available from the authors upon request

Table 2. Conditional average wage returns

	OLS	RE
Full-time schooling	0.089	0.105
	(0.000)	(0.000)
Part-time schooling	0.019	0.027
	(0.000)	(0.000)

Notes: P-values based on robust standard errors in parentheses

Table 3. Conditional quantile wage returns

	QR		REQR	
	Full-time schooling	Part-time schooling	Full-time schooling	Part-time schooling
Q10	0.051	0.003	0.082	0.020
	(0.002)	(0.000)	(0.000)	(0.000)
Q25	0.067	0.010	0.091	0.024
	(0.004)	(0.003)	(0.001)	(0.002)
Q50	0.085	0.019	0.103	0.028
	(0.003)	(0.006)	(0.005)	(0.003)
Q75	0.098	0.022	0.117	0.031
	(0.007)	(0.006)	(0.000)	(0.000)
Q90	0.0117	0.025	0.129	0.033
	(0.007)	(0.005)	(0.000)	(0.001)

Notes: P-values based on bootstrapped standard errors in parentheses (100 reps.)

Table 4. Impacts on conditional wage dispersion (Q90-Q10)

	QR	REQR
Full-time schooling	0.066	0.047
	(0.000)	(0.000)
Part-time schooling	0.022	0.013
	(0.000)	(0.000)

Notes: P-values based on t-test statistics in parentheses