Full-time schooling, part-time schooling, and wages: returns and risks in Portugal [*]

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Abstract
The standard wage equation proposed by Mincer (1974) assumes that individuals start working after leaving school, which is not the actual case for many people. Using longitudinal data on Portuguese male workers, former working students, we estimate the total impact of an additional year of full-time schooling on both the mean and the shape of the conditional wage distribution. The same exercise is also performed for part-time schooling. We find that the conditional average earnings return to one year of part-time schooling is *much lower* than the analogous return to one year of full-time schooling. However, the conditional wage risk implied by one year of part-time schooling is *much lower* than the analogous risk implied by one year of full-time schooling, thus complicating policy considerations. Nevertheless, we find evidence that the full-time schooling strategy *dominates*, in conditional wage distribution, the part-time schooling strategy, meaning that the choice of working while enrolled in school does not ultimately pay.

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

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1. Introduction

The seminal work by Jacob Mincer (1974) on *Schooling, Experience and Earnings* is the starting point of a large body of literature dealing with the estimation of an individual-level wage equation where the logarithm of hourly earnings 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 has to do with 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 Audrey Light (2001, p. 65), "students often accumulate substantial work experience before leaving school".

A recent 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 of controlling for in-school work experience when estimating the Mincerian return to schooling is relatively recent. Light (2001) uses data from the US National Longitudinal Survey of Youth and finds that the lack of control for in-school work experience implies a substantial overestimation of the Mincerian return to schooling.

Of course, the study by Audrey Light is not the only, nor the first study in the field. On the contrary, the field is relatively rich in contributions aiming at measuring the earnings return to in-school work. From a theoretical point of view, the academic debate on this issue 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. Nevertheless, an important study by Hotz et al. (2002) questions this whole body of evidence because unobserved heterogeneity and sample selectivity are not controlled for. Indeed, the authors find that controlling for these two factors completely eliminates the positive impact of in-school work on future earnings.

Another striking feature of the empirical literature, at academic level, concerns with being almost exclusively related to the case of the United States. A recent paper 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 existing literature suggests that the earnings return to an additional year of full-time schooling is much higher than the earnings return to an additional year of either in-school work or part-time schooling, which are two sides of the same coin. However, despite a relatively high number of contributions, we believe that some important information is still missing in the existing literature. This information concerns with the estimation of the wage risk of full-time education compared to part-time education. As a matter of example, if an additional year of full-time schooling pays more than an additional year of part-time schooling in terms of average future wage returns, the latter may involve less wage risk than the first. That is, there may be a trade-off between risk and return that the literature has not explored yet.

Starting from the latter consideration, this paper attempts to identify the total average impact of both full-time schooling and part-time schooling on earnings, also comparing associated wage risks. Hence, from an academic point of view, our paper contributes to the ongoing debate on the return-risk link in education (among others, see Levhari and Weiss, 1974; Pereira and Martins, 2002; Hogan and Walker, 2003; Harmon et al., 2003; Hartog et al., 2004; Christiansen et al., 2006; Andini, 2007a).

Specifically, we aim at answering, in a different way than suggested so far, the question of whether the choice of working while enrolled in school actually pays. As we will see, based on Portuguese data, the answer is complex. Considering average wage returns only, we answer "no". Therefore, the answer is in line with earlier findings by both Hotz et al. (2002) and Häkkinen (2006). However, considering wage risks only, we answer "yes". Therefore, considering both returns and risks, the answer to our main research question may appear controversial. Nevertheless, we find that the full-time schooling strategy dominates, in conditional wage distribution, the part-time schooling strategy, thus providing an economic reason for ultimately answering "no".

2. Theoretical background

If the average wage return to full-time schooling is clearly higher than the average wage return to part-time schooling as suggested by the existing literature, why does the phenomenon of in-school work continue to exist? There are multiple ways of answering this question. For the purpose of this paper, we find interesting the exercise of focusing on return-risk considerations, using a simple model of choice based on unconditional moments.

Let us think at full-time schooling and part-time schooling as two different assets providing random wage returns, say $\tilde{W}_1 \sim (\beta_1, \sigma_1^2)$ and $\tilde{W}_2 \sim (\beta_2, \sigma_2^2)$ respectively. Analogously, let as think at schooling as a portfolio of these two assets providing a random wage return, say $\tilde{W} \sim (\beta, \sigma^2)$.

Further, following the existing evidence, let us assume that full-time schooling provides a higher average wage return than part-time schooling, i.e. $\beta_1 > \beta_2$. In addition, let us assume that the correlation coefficient between the wage returns to full-time schooling and part-time schooling is equal to ρ. Finally, let us suppose that an individual cares about the mean β and the variance σ^2 of the random wage return of the schooling portfolio, i.e. the individual utility function is specified as $U(\beta, \sigma^2)$ with $U'(\beta) > 0$ and $U'(\sigma^2) < 0$.

Under the hypothesis that an individual maximizes his/her mean-variance utility function, which share of schooling years should be optimally invested in full-time education and in part-time education?

To answer this question, we must first note that the individual faces the following constraint:

$$(1) \qquad \tilde{W}S = \tilde{W}_1 S_1 + \tilde{W}_2 S_2$$

where S_1 is the number of schooling years invested in full-time schooling, and S_2 is the number of schooling years invested in part-time schooling. For sake of simplicity, we assume that the total number of schooling years S is determined outside the model.

Expression (1) simply tells us that the total random wage return provided by S years of schooling must be equal the total random wage return provided by S_1 years of full-time schooling plus the total random wage return provided by S_2 years of part-time schooling.

Dividing both sides of expression (1) by S, we obtain the following expression:

$$(2) \qquad \tilde{W} = x_1\tilde{W}_1 + x_2\tilde{W}_2$$

where $x_1 = \frac{S_1}{S}$ is the share of schooling years invested in full-time education, while $x_2 = 1 - x_1$ is the share of schooling years invested in part-time education (note that the expression $S = S_1 + S_2$ holds).

Using (2), we can easily show that both $\beta = E(\tilde{W})$ and $\sigma^2 = VAR(\tilde{W})$ depend on x_1, according to the following expressions:

$$(3) \qquad \beta = x_1\beta_1 + (1 - x_1)\beta_2$$

and

$$(4) \qquad \sigma^2 = x_1^2\sigma_1^2 + (1 - x_1)^2\sigma_2^2 + 2x_1(1 - x_1)\rho\sigma_1\sigma_2 .$$

Therefore, the economic problem of the individual who chooses the optimal share of schooling years to be invested in full-time schooling in order to maximize his/her mean-variance utility function turns out to be the following simple one:

$$(5) \qquad \underset{0 \le x_1 \le 1}{\text{Max}} \quad U(\beta, \sigma^2) \, .$$

Under appropriate parameters' conditions, problem (5) admits the following *internal* solution:

$$(6) \qquad x_1{*} = \frac{\dfrac{\beta_1 - \beta_2}{2\alpha} + \sigma_2^2 - \rho\sigma_1\sigma_2}{\sigma_1^2 + \sigma_2^2 - 2\rho\sigma_1\sigma_2}$$

where $\alpha = -\dfrac{U'(\sigma^2)}{U'(\beta)}$ represents a degree of wage risk aversion.

This simple model, mainly inspired by an earlier model for skills developed by Hartog and Vijverberg (2006), helps to show that, although the average wage return to full-time education is higher than the average wage return to part-time education ($\beta_1 > \beta_2$), an individual may optimally choose to spend a share of schooling years as a working student, say $x_1{*} = 0.6$ implying $x_2{*} = 0.4$, because the wage risks involved in both full-time schooling and part-time schooling also matter for the choice (among other things).

Therefore, it is important to estimate not only the conditional average wage returns to both full-time schooling and part-time schooling but also the conditional wage risk involved in both full-time education and part-time education. This is what we do in the next section.

3. Data, empirical model and results

We use data on Portuguese male workers from the European Community Household Panel, from the wave of 1994 to the wave of 2001, and focus on a sample of former working students. The sample is described in Table 1.

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

$$(7) \qquad \ln w_{it} = \beta_0 + \beta_1 school_i + \beta_2 potwork_{it} + \beta_3 potwork_{it}^2 + \xi_{it}$$

where $\ln w$ represents the natural logarithm of hourly earnings, $school$ represents schooling years, and $potwork$ stands for potential work-experience computed as usual (individual age minus schooling years minus six). Letter i represents the individual dimension, while letter t represents the time dimension (annual, in our data-set).

For the purpose of this paper, we suggest two simple departures from the above empirical setting. First, rather than potential labour-market experience, we compute actual full-time labour-market experience. The latter is given by the number of full-time working years actually accumulated by an individual at the date of the interview. Let us label this variable as $fullwork$. Second, we distinguish between years of full-time schooling, labelled as $fullschool$, and years of part-time schooling, labelled as $partschool$.

In addition, as usual with longitudinal data, instead of just considering a fixed common intercept, we allow for the existence of individual-specific intercepts in order to capture individual heterogeneity, due to different abilities, costs of borrowing, labour-market luck, and so on. Moreover, we use wave dummies to keep year heterogeneity into account. Therefore, we estimate the following empirical model:

$$(8) \qquad ln\, w_{it} = \beta_0 + \beta_1\, fullschool_i + \beta_2\, partschool_i + \beta_3\, fullwork_{it} + \beta_4\, fullwork_{it}^2 + \beta_i + \beta_t + \xi_{it}$$

using the random-effects estimator (RE) and the between-effects estimator (BE). Further, we provide pulled estimates based on the ordinary-least-squares estimator (OLS), thus disregarding the longitudinal structure of the data-set. Finally, in order to evaluate and compare the wage risks implied by both full-time education and part-time education, we also use the quantile-regression estimator (QR) due to Koenker and Bassett (1978). Specifically, we provide estimates for a model of the following type:

$$(9) \qquad ln\, w_{it} = \beta_{0\theta} + \beta_{1\theta}\, fullschool_i + \beta_{2\theta}\, partschool_i + \beta_{3\theta}\, fullwork_{it} + \beta_{4\theta}\, fullwork_{it}^2 + \beta_{t\theta} + \xi_{it\theta}$$

where θ represents the conditional wage-distribution decile. Hence, following a seminal contribution by Buchinsky (1994) for the United States, we contribute 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; Andini, 2007b).

Note that we focus on the estimation of *total* returns, meaning that all direct and indirect effects of education, either full-time or part-time, on earnings are captured by just two coefficients, β_1 and β_2 (see Pereira and Martins, 2004; Andini, 2007c).

Estimation results on conditional average returns, based on the RE estimator, are reported in Table 2 (0.085 vs. 0.018). Results based on the BE estimator are presented in Table 3 (0.084 vs. 0.020). As we can observe, the earnings return to an additional year of full-time schooling is much 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. In addition, Table 4 shows that the OLS estimator is fully in line with the RE estimator and with the BE estimator, suggesting that the role played by individual unobserved heterogeneity, in our specific application, is likely to be relatively small (0.089 vs. 0.019).

Figure 1 presents quantile-regression estimates of β_1 and β_2 at each decile of the conditional wage distribution. The graph in Figure 1 is obtained using a specific STATA module written by Azevedo (2004). We measure the wage risk as usual in the literature, i.e. as difference between the return at the ninth decile and the return at the first decile. Note, in Table 5, that the wage risk involved in full-time education is almost 4 times bigger than the wage risk involved in part-time education, meaning that there is clear evidence of a trade-off between risk and return. Nevertheless, the return to an additional year of full-time schooling at the first decile (0.052) is higher than the return to an additional year of part-time schooling at the ninth decile (0.031), meaning that the full-time schooling strategy dominates, in conditional wage distribution, the part-time schooling strategy.

The latter results seem to be robust to endogeneity issues. Table 6 presents two-stage-least-squares estimates, using indicator-variables of birth years as instruments[1] for our four potentially endogenous regressors. The results confirm that the average return to full-time schooling is bigger than the average return to part-time schooling (0.098 vs. 0.023). Finally, instrumental-variable quantile regressions in Figure 2, performed using the procedure suggested by Arias et al. (2001), confirm that the full-time schooling strategy dominates the part-time schooling strategy. Again, the full-time schooling return at the first decile (0.044) is higher than the part-time schooling return at the ninth decile (0.030, not statistically significant).

4. Conclusions

In line with what one may reasonably expect from previous research, we find 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 mean earnings return to one additional year of full-time schooling is four times larger than the mean earnings return to one additional year of part-time schooling. This suggests that the choice of working while enrolled in school is not worth, in terms of future average labour-market rewards, because one year of full-time schooling provides the same average total return as four years of part-time schooling.

[1] This choice is motivated by the fact that, as explained in Table 1 (Note), all our potentially endogenous regressors are age-related variables. Therefore, the birth years of the individuals in the sample are likely to be correlated with our potentially endogenous regressors and are, of course, independent from the wage level. Although not reported, first-stage statistics confirm this view and are available from the authors upon request.

If these results would imply the same wage risk, 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 wage risk, thus complicating policy considerations. Indeed, the wage risk of part-time schooling is much lower than the wage risk of full-time schooling, implying that that educational policies fostering full-time education in Portugal would significantly increase within-groups wage inequality in the future. Putting it differently, the existence of different wage risks associated with full-time education and part-time education provides an economic reason for the existence of special curricula for working students, otherwise not justified by the empirical evidence on the average wage returns to part-time schooling.

Nevertheless, since the full-time schooling strategy dominates, in conditional wage distribution, the part-time schooling strategy, our final answer to the main research question of this paper is not controversial. Does the choice of working while enrolled in school actually pay? We answer “no”.

A final note is about the fact that the Portuguese working students continue to exist (representing, on average, around 27 percent of former students in our data-set), although our analysis suggests that part-time schooling does not ultimately pay for being associated with a dominated conditional wage distribution. Hence, the reader may wonder whether our results are at odds with the evidence of existing working students. Again, the answer is “no” and the reasons are multiple. First, we estimate ex-post returns and risks while people make their choices based on ex-ante returns and risks (which cannot be estimated). Second, the choice of part-time schooling not only depends on the return-risk combination but also on the individual degree of risk aversion (although we control for individual unobserved heterogeneity). Third, the paper disregards a number of financial issues which are likely to affect the part-time schooling choice, such as borrowing constraints, imperfect capital markets, university fees, scholarships, and so on. Forth, there are many non-financial factors that also affect the allocation of time between work and study. Finally, our results are consistent with 2005 data showing that Portugal has the lowest percentage of higher-education working students in a sample of eleven European countries. The share is around 20 percent in Portugal, which is ten percentage points lower than the share of the country with the second lowest share, i.e. Italy with 30 percent (HIS, 2005).

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Table 1. Summary sample statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
lnw	3930	6.622962	.6530738	3.641526	10.02374
fullschool	3930	9.994911	4.09041	3	24
partschool	3930	8.311196	8.247822	1	48
fullwork	3930	16.3743	12.46107	0	54

Note

In order to derive the variables fullwork, partschool and fullschool, 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. Specifically, we select a sample of Portuguese male workers such that PT023 is strictly higher than PE039, and define the above-referred variables as follows: fullwork as PD003-PT023, partschool as PT023-PE039, fullschool as PE039-6. Therefore, it is not surprising that the sample descriptive statistics report that Portuguese male workers, former working students, have on average 10 years of full-time schooling and 8 years of part-time schooling. These numbers, indeed, do not necessarily reflect successfully completed years of schooling. This is an interesting point because the main criticism to in-school work is exactly the argument that working while enrolled in school may delay education achievements.

Table 2. Random effects

Random-effects GLS regression — Number of obs = 3930
Group variable (i): pid — Number of groups = 1157

R-sq: within = 0.2838 — Obs per group: min = 1
between = 0.2591 — avg = 3.4
overall = 0.2892 — max = 8

Random effects u_i ~ Gaussian — Wald chi2(11) = 1505.34
corr(u_i, X) = 0 (assumed) — Prob > chi2 = 0.0000

lnw	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
fullwork	.0208312	.0023712	8.79	0.000	.0161838	.0254786
fullwork2	-.0001702	.0000515	-3.31	0.001	-.0002711	-.0000694
fullschool	.0851538	.0043278	19.68	0.000	.0766714	.0936361
partschool	.0183835	.001454	12.64	0.000	.0155336	.0212334
_Iwave1	-.3914315	.0184576	-21.21	0.000	-.4276078	-.3552551
_Iwave2	-.3354851	.0177141	-18.94	0.000	-.3702041	-.300766
_Iwave3	-.2666482	.0172683	-15.44	0.000	-.3004934	-.232803
_Iwave4	-.2251006	.01706	-13.19	0.000	-.2585375	-.1916637
_Iwave5	-.1978512	.0156936	-12.61	0.000	-.2286101	-.1670922
_Iwave6	-.1328446	.0150539	-8.82	0.000	-.1623497	-.1033395
_Iwave7	-.0447158	.0149217	-3.00	0.003	-.0739619	-.0154697
_cons	5.508158	.0700647	78.62	0.000	5.370834	5.645482
sigma_u	.51821363					
sigma_e	.21428108					
rho	.85398421	(fraction of variance due to u_i)				

test fullschool = partschool
chi2(1) = 278.89
Prob > chi2 = 0.0000

Table 3. Between effects

Between regression (regression on group means) Number of obs = 3930
Group variable (i): pid Number of groups = 1157

R-sq: within = 0.0925 Obs per group: min = 1
between = 0.2742 avg = 3.4
overall = 0.2601 max = 8

F(11,1145) = 39.32
sd(u_i + avg(e_i.))= .5385587 Prob > F = 0.0000

lnw	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
fullwork	.0292101	.0043927	6.65	0.000	.0205915	.0378288
fullwork2	-.0004279	.0001013	-4.22	0.000	-.0006267	-.0002291
fullschool	.0840968	.0043851	19.18	0.000	.0754931	.0927005
partschool	.0203842	.00216	9.44	0.000	.0161461	.0246222
_Iwave1	-.3068317	.0911674	-3.37	0.001	-.4857055	-.1279578
_Iwave2	-.234415	.1166373	-2.01	0.045	-.4632619	-.0055682
_Iwave3	-.5260609	.1356939	-3.88	0.000	-.7922974	-.2598243
_Iwave4	-.0453428	.123345	-0.37	0.713	-.2873504	.1966648
_Iwave5	-.1804502	.087127	-2.07	0.039	-.3513967	-.0095036
_Iwave6	-.1185844	.1046138	-1.13	0.257	-.3238406	.0866718
_Iwave7	-.172846	.1221256	-1.42	0.157	-.4124611	.066769
_cons	5.470078	.0948218	57.69	0.000	5.284034	5.656122

test fullschool = partschool
F(1, 1145) = 211.93
Prob > F = 0.0000

Table 4. Ordinary least squares

Linear regression

Number of obs	=	3930
F(11, 3918)	=	132.64
Prob > F	=	0.0000
R-squared	=	0.2968
Root MSE	=	.54844

lnw	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
fullwork	.0339942	.0023772	14.30	0.000	.0293336	.0386549
fullwork2	-.0005111	.0000539	-9.47	0.000	-.0006168	-.0004053
fullschool	.0895028	.0027012	33.13	0.000	.084207	.0947987
partschool	.0191103	.0011407	16.75	0.000	.0168739	.0213468
_Iwave1	-.3788325	.0356636	-10.62	0.000	-.4487534	-.3089115
_Iwave2	-.3291732	.0343903	-9.57	0.000	-.3965977	-.2617487
_Iwave3	-.2744965	.034556	-7.94	0.000	-.342246	-.2067471
_Iwave4	-.2159065	.0366836	-5.89	0.000	-.2878273	-.1439857
_Iwave5	-.1646828	.033975	-4.85	0.000	-.2312931	-.0980725
_Iwave6	-.1184582	.0336265	-3.52	0.000	-.1843853	-.0525312
_Iwave7	-.0412331	.0353307	-1.17	0.243	-.1105014	.0280352
_cons	5.420886	.0456222	118.82	0.000	5.33144	5.510331

test fullschool = partschool
F(1, 3918) = 674.48
Prob > F = 0.0000

Table 5. Quantile regression

Simultaneous quantile regression — bootstrap(20) SEs

Number of obs = 3930
.10 Pseudo R^2 = 0.1034
.90 Pseudo R^2 = 0.2125

lnw	Coef.	Bootstrap Std. Err.	t	P>|t|	[95% Conf.	Interval]
q10						
fullwork	.0192452	.0044459	4.33	0.000	.0105287	.0279616
fullwork2	-.0003358	.0001129	-2.97	0.003	-.0005572	-.0001144
fullschool	.0523922	.0040877	12.82	0.000	.044378	.0604063
partschool	.0098558	.0013591	7.25	0.000	.0071912	.0125204
_Iwave1	-.3994209	.0714292	-5.59	0.000	-.5394628	-.2593789
_Iwave2	-.3351579	.0532195	-6.30	0.000	-.4394985	-.2308173
_Iwave3	-.276591	.0636758	-4.34	0.000	-.4014318	-.1517503
_Iwave4	-.2549399	.0478544	-5.33	0.000	-.3487618	-.1611179
_Iwave5	-.1843033	.0518817	-3.55	0.000	-.286021	-.0825857
_Iwave6	-.116931	.0563719	-2.07	0.038	-.2274521	-.00641
_Iwave7	-.0354948	.073436	-0.48	0.629	-.1794712	.1084816
_cons	5.438439	.0645124	84.30	0.000	5.311958	5.56492
q90						
fullwork	.0550101	.0052068	10.56	0.000	.0448018	.0652185
fullwork2	-.0007545	.0001301	-5.80	0.000	-.0010096	-.0004995
fullschool	.1187404	.0060719	19.56	0.000	.106836	.1306449
partschool	.0318043	.0021758	14.62	0.000	.0275385	.0360701
_Iwave1	-.4127351	.0702157	-5.88	0.000	-.5503979	-.2750724
_Iwave2	-.2936352	.0768471	-3.82	0.000	-.4442993	-.1429711
_Iwave3	-.2154177	.0678516	-3.17	0.002	-.3484455	-.0823898
_Iwave4	-.130763	.0887883	-1.47	0.141	-.3048386	.0433127
_Iwave5	-.1508407	.065274	-2.31	0.021	-.278815	-.0228664
_Iwave6	-.1457818	.0735863	-1.98	0.048	-.2900529	-.0015106
_Iwave7	-.0367713	.0451008	-0.82	0.415	-.1251945	.0516519
_cons	5.459747	.0986907	55.32	0.000	5.266257	5.653237

test [q10]fullschool = [q90]fullschool
F(1, 3918) = 97.26
Prob > F = 0.0000

test [q10]partschool = [q90]partschool
F(1, 3918) = 100.05
Prob > F = 0.0000

Table 6. Two stage least squares

Instrumental variables (2SLS) regression

Number of obs	= 3930
F(11, 3918)	= 90.14
Prob > F	= 0.0000
R-squared	= 0.2653
Root MSE	= .56058

lnw	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
fullwork	.0596617	.011643	5.12	0.000	.0368348	.0824887
fullwork2	-.0011643	.0002181	-5.34	0.000	-.0015918	-.0007368
fullschool	.0989281	.0133004	7.44	0.000	.0728517	.1250045
partschool	.0236904	.0114963	2.06	0.039	.0011511	.0462297
_Iwave1	-.3944854	.0480359	-8.21	0.000	-.4886631	-.3003077
_Iwave2	-.3477386	.0445069	-7.81	0.000	-.4349975	-.2604798
_Iwave3	-.2912321	.0420338	-6.93	0.000	-.3736423	-.2088219
_Iwave4	-.2398407	.0442276	-5.42	0.000	-.326552	-.1531294
_Iwave5	-.1595099	.0378712	-4.21	0.000	-.233759	-.0852609
_Iwave6	-.1185794	.0354256	-3.35	0.001	-.1880337	-.0491251
_Iwave7	-.0379593	.0369222	-1.03	0.304	-.1103478	.0344292
_cons	5.152926	.1403473	36.72	0.000	4.877765	5.428087

test fullschool = partschool
F(1, 3918) = 17.28
Prob > F = 0.0000

Figure 1. Quantile regression

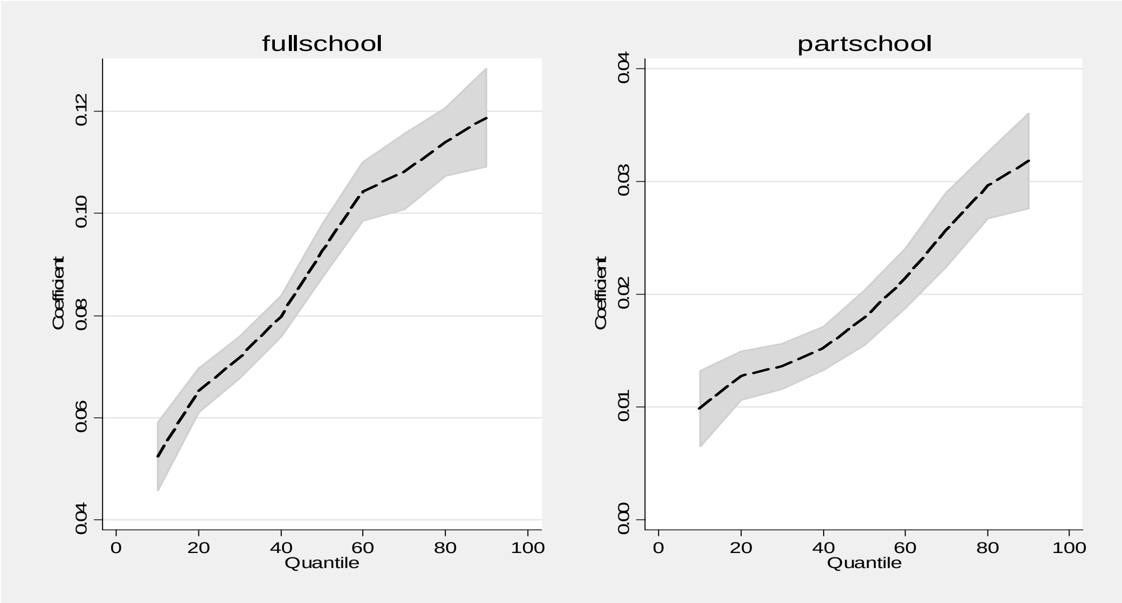

Figure 2. Instrumental variable quantile regression