Documentos de Trabajo

Returns to schooling in Uruguay

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Abstract

In this paper we analyze the economic returns to schooling in Uruguay. Instrumental variables are used to estimate mean and quantile regressions. An indicator of whether an Internet connection is available at home is used as an instrument for the years of schooling of the household head. The evidence shows that the simple Mincer OLS estimates are downward biased. When estimates are controlled for measurement error in schooling reports the results indicate that an additional year of schooling increases wage rates by 22 percent.

Key words: returns to schooling, schooling premium
JEL: C13, I21, J24, J31

Resumen

Este artículo analiza la rentabilidad de la educación en el Uruguay. Se utilizan variables instrumentales para estimar regresiones medias y cuantílicas. Un indicador de la disponibilidad de conexión a Internet en el hogar es usado como instrumento para los años de educación del jefe de hogar. La evidencia analizada muestra que las estimaciones MCO de la ecuación de Mincer están sesgadas hacia cero. Las estimaciones que controlan por la presencia de errores de medida en el relevamiento de los años de educación indican que un año adicional de educación aumenta el salario en 22 por ciento.

Palabras claves: retornos de la educación, prima salarial

JEL: C13, I21, J24, J31

1 Introduction

How much to invest in education is one of the most important economic decisions that individuals and policy-makers have to face. Hundreds of studies in many different countries and time periods have confirmed that better-educated individuals earn higher wages, suffer less unemployment and work in more prestigious occupations than their less-educated counterparts (Card, 1999). Schultz (2003) argues that there are three interrelated aspects involved in the design of an efficient and equitable educational system. First, the productivity of similar workers with different levels of schooling must be assessed. Second, the personal distribution of the benefits of an educational program should not exacerbate economic inequalities, and should, if possible, reduce them. Third, the specified levels of education should be produced at the lowest possible private and public cost. In this paper we explore the first of these aspects by estimating the private returns to education in Montevideo.

Two econometric questions arise from the empirical study of returns to schooling (Card, 1999; Ashenfelter and Krueger, 1994; Griliches, 1977 and 1979). First, as is common knowledge, the effect of survey measurement error in schooling produces an attenuation bias in the estimates of the causal effect of education. Second, there is an unobservable heterogeneity problem, i.e. the expected relationship between unobservable ability and schooling made for an upward bias in any estimated effect.

In this paper we propose to overcome these estimation problems by using an instrumental-variables approach. An indicator of whether an Internet connection is available at home is used as an instrument for the years of schooling of the household head.

The data used in this study are drawn from the Uruguayan Household Survey from 2001 to 2005 (Encuesta de Hogares, Instituto Nacional de Estadística, Uruguay). The sample we used here consists of male heads of households aged 35-44 who are private-sector full-time paid workers resident in Montevideo.

The results indicate that the economic returns to schooling in Uruguay may have been underestimated in the past. We found that, on average, each year of additional schooling

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correlates to an additional 22 percent in earnings. This is 10 to 12 points higher than the Bucheli and Furtado (2000), Miles and Rossi (1999) and Casacuberta (2005) estimates, but it is important to note that a different sample was used. Thus, in order to evaluate the attenuation bias associated with the presence of measurement error the comparison must be made with respect to the 14 percent premium OLS estimate from the selected sample over the period 2001-2005.

There are six sections to the remaining of this paper. In the next we present a brief survey of previous Uruguayan estimates of the returns to schooling. Section 3 deals with the description of the dataset. Section 4 examines the econometric aspects of returns to schooling estimates. Section 5 presents the equation to be estimated, and the strategies we propose to overcome those problems. The results are analyzed in Section 6, and in Section 7 our conclusions are presented.

2. Empirical evidence about returns to schooling in Uruguay

There were many studies of the returns to schooling in Uruguay during the 1980s and 1990s (see Bucheli (2000) for an exhaustive survey). The basic equation employed corresponds to a simple Mincer (1974) equation; i.e. log hourly wage rates is the dependent variable, and regressors include education level, years of work experience and its square, and other controls such as gender, tenure and industry. Estimates by Bucheli and Furtado (2000) indicate that in the 1990s an additional year of schooling increased wage rates by an average of 9.6 percent.

They also found that returns to schooling decreased from 1986 to 1989 and then rose until 1995. As a result the education premium was higher in the 1990s than in the 1980s. An additional aspect of the situation that was addressed by Bucheli and Furtado (2000) is whether that premium is constant for all education levels. They included a quadratic term in years of schooling and found that the respective coefficient is not significantly different than zero before 1994 but is positive and increases after that year.

Miles and Rossi (1999) estimated quantile regressions so as to analyze how the returns to schooling vary among different socioeconomic groups. They estimated the premium to an additional year of schooling measured for each of the five quintiles of empirical wage distribution.

These authors found a U-shaped relationship between education premium and 3 quintiles. That is, the return to an additional year of schooling is higher in initial and tertiary education than in secondary education. Finally, they concluded that the returns to schooling in the highest quintile increased significantly in the 1990s.

Casacuberta (2005) uses OLS regressions and finds that the returns to education go from 8 to 10 percent during the nineties and from 10 to 12 in the period 2000-2003.

Bucheli and Casacuberta (2001), Torello and Casacuberta (1997) and Bucheli (1992) suggest that the returns to schooling vary for different numbers of years of schooling. In particular, they argue that there is a "degree premium" associated with completing an

education cycle, so they proposed to estimate the returns to schooling using dummy variables for each education level. Arim and Zopollo (2000) used the same approach and concluded that the premium to the highest education level as against primary education decreased from 1986 to 1991 and then increased until 1996. The evidence they analyzed also showed that the premium of the secondary cycle was almost constant over that period.

Bucheli et al (2000) found that the returns to schooling increase over the life cycle. However they also showed the rise in the returns to education in the 1990s especially favoured the earnings of the youngest cohort. Finally, some studies have shown that the return to schooling is higher among private-sector workers (Trylesinky, 1991; Bucheli, 1994 and 1995).

3 Data

The data used in this study are drawn from the Uruguayan Household Survey for 2001 to 2005 (Encuesta de Hogares, Instituto Nacional de Estadística, Uruguay). The survey frame is the civilian population of Uruguay living in housing units in urban areas, decomposed into one survey for the metropolitan area of Montevideo and another one for the population living in cities in the rest of Uruguay.

The survey includes information about individual characteristics such as age, gender, labour status, education, wage rates and hours worked. The survey asks for the completed years of education at every level the individual has undertaken (primary, secondary, vocational, teacher's schools and university o similar). During the period covered by the sample used (2001-2005) there were no changes to the questions about education or to those about wage rates or hours worked.

It is important to note that a question about the availability of an Internet connection at home is introduced for the first time in the 2001 questionnaire and has featured in subsequent years. The sample we used consisted of male heads of households aged 35-44 and resident in Montevideo. We only included those who had positive remuneration in the month preceding the interview, i.e. at least one-month tenure, and who had worked at least 34 hours in the week before the interview. We restricted the sample to those who were

employed in the private sector and excluded entrepreneurs, the self-employed and those who worked in the public sector.

The variable of interest is the real hourly wage, obtained as the remuneration and benefits in the month before the interview divided by four times the hours worked in the week prior to the interview. We assumed that the hours worked in the week prior to the interview are the same for the whole month before the interview. In Table 1 we present some descriptive statistics of the main variables.

4 Econometric aspects

Recent studies of education and wage determination have almost always been carried out in the framework of Mincer's (1974) human capital earning function (Card, 1999). According to this model, the log of wage rates (w) in a given time period can be decomposed into an additive function of a linear education term and a quadratic working experience term,

$$\ln(w_i) = \varphi + \alpha S_i^* + \beta \exp_i^* + \gamma \left(\exp_i^*\right)^2 + \in_i \tag{1}$$

where S_i^* is true schooling, $\exp_i^*$ is years of work experience, $\in_i$ is an unobservable random variable, and α, β and γ are unknown parameters to be estimated.

In the early literature following the appearance of Mincer's approach, equation [1] was commonly estimated by means of ordinary least square (OLS). This estimation technique assumes that the explanatory variables are uncorrelated with the unobserved disturbance in the equation which for various reasons might not be fulfilled. Many studies have found conclusive evidence that the measurement error in schooling levels is considerable (see, e.g., Ashenfelter and Krueger, 1994; Griliches, 1977 and 1979). Moreover, various researchers have raised the question of whether the observed positive correlation between schooling and wage rates is caused by education or whether it is due to a correlation between schooling and unobserved worker ability.

Therefore two main econometric questions arise in the empirical study of returns to schooling. First, it is necessary to deal with the effect of survey measurement error in

schooling. Measurement error in schooling would be expected to lead to a downward bias in any OLS estimation of the relationship between schooling and earnings. Second, there is an unobservable heterogeneity problem, i.e. the expected relationship between unobservable ability and schooling could give rise to a bias in any estimated effect.

Three approaches have been used to try to deal with these potential problems (Ashenfelter et al, 1999; Card, 1999). These are, first, the use of a proxy variable (like IQ tests) for unobservable ability, second, using estimates based on the earnings and schooling of siblings and twins, and third, following an instrumental-variable estimation strategy.

The first approach deals with the issue of ability bias by including explicit measures that proxy for unobserved ability. Examples of these proxies are IQ tests and other tests of that type (Griliches, 1977; Griliches and Mason, 1972). The results of these studies have suggested that there is an upward bias in results that lack an ability measure. The method that involves adding ability proxies has been criticized, however, because it is extremely difficult to develop ability measures that are not themselves determined by schooling. When the ability measure is itself influenced by schooling, the use of ability proxies will, in fact, give a downward bias to estimates of returns.

The siblings or twins approach is based on the belief that siblings are more alike than a randomly selected pair of individuals since they share the same heredity, financial support, peer influences, and environment. This approach attempts to overcome omitted ability bias by estimating the returns to schooling from differences between siblings or twins as regards levels of schooling and earnings. Studies based on sibling or twin comparisons have been criticized for various reasons. First, if ability has an individual component as well as a family component, and this is not independent of schooling level, the in-family approach may not yield estimates that are less biased than OLS estimates. Second, if schooling is measured with error, this will account for a larger fraction of the differences between the twins than across the population as a whole. This would mean that the bias from measurement error in schooling is likely to increase when differences between twins are used, which means that estimates involving twins will be biased downwards. Following the lead given by Ashenfelter and Krueger (1994) in their innovative paper, many contributions

to siblings literature have attempted to deal with the measurement error problem by collecting numerous measures of schooling, by questioning the siblings about each other or by using independent measures of error variances to adjust the estimates (see, e.g., Ashenfelter and Rouse, 1998; Miller et al, 1995; Rouse, 1997). Many of these in-twin studies suggest that ability bias is relatively small, although this is only the case when measurement error has been controlled. Ashenfelter and Krueger (1994) controlled for measurement error using instrumental variable regressions and found that the estimates of the returns to schooling were nearly double the simple OLS estimate.

Finally, the instrumental variable approach includes instrumental variable estimates of the returns to education based on institutional features of the education system and estimates based on either controlling for family background or using family background as an instrument for schooling (Card, 1999).

One of the most important new directions of research in the recent literature on schooling is the use of institutional features of the schooling system as a source of credible identifying information for disentangling the causal effects of schooling.

There are various studies that use the instrumental variable approach (for a detailed survey see Card, 1999). Angrist and Krueger (1991), with data from the United States, use the individual's quarter of birth (interacted with the year of birth or the State of birth) as an instrument for schooling. Their IV estimates of the returns to education are typically higher than the corresponding OLS estimates.

Staiger and Stock (1997) re-analyze the 1980 census samples used by Angrist and Krueger and compute a variety of asymptotically valid confidence intervals for standard IV and limited information maximum likelihood (LIML) estimates. Their estimates are somewhat above the corresponding conventional IV estimates and 50-70 percent higher than OLS estimates.

Card (1995) finds that when college proximity is used as an instrument for schooling in the National Longitudinal Survey (NLS) Young Men sample, the resulting IV estimator is considerably higher than the corresponding OLS estimator, although this study is rather

imprecise. Card also propose an alternative specification that uses an interaction of college proximity with family background variable as an instrument for schooling, and includes college proximity as a direct control variable. The IV estimate from this interacted specification is somewhat lower than the estimate using college proximity alone, but still 30 percent above the OLS estimate.

Harmon and Walker (1995) examined the returns to education among a relatively large sample of British male household heads. As instrumental variables for schooling, these authors used a pair of dummy variables that index changes in the minimum school leaving age in Britain (from 14 to 15 in 1947, and from 15 to 16 in 1973). Their IV estimate is 2.5 times higher than their OLS estimate. Card (1999) highlights the fact that there are several aspects of their estimation strategy that suggest their estimates may be upwardly biased.

Finally, there are many studies that use measures for family background (typically parental education or education of a sibling) as either a control variable or an instrument in models of the returns to education (Card, 1995; Card, 1999; Conneely and Uusitalo, 1997; Ashenfelter and Zimmerman, 1997; Miller *et al*, 1995; Ashenfelter and Rouse, 1998; Isacsson, 1997). Their results show that the addition of parental education as a control variable lowers the measured return to education, while the use of parental education as an instrument for years of schooling increases the estimation of the schooling premium.

5. Econometric approach

The basic framework is given by equation [1]. A conventional assumption is that observed schooling (S_i) differs from true schooling (S_i^*) by an additive error (v_i),

$$S_i = S_i^* + v_i \tag{2}$$

where v_i is a random variable that satisfies $E[v_i] = E[S_i^* v_i] = 0$, and $E[v_i^2] = \sigma_v^2$

Another common assumption in the literature is that $\in_i$, the disturbance term of equation [1], is a random two component error term,

$$\in_i = \eta_i + \varepsilon_i \tag{3}$$

We assume that $\eta_i \square \left(0, \sigma_\eta^2\right)$ represents unobservable characteristics of the individual (such as ability or family background) that are time invariant and are potentially correlated to S_i^*. On the other hand $\varepsilon_i \square \left(0, \sigma_\varepsilon^2\right)$ captures an unobservable agent's characteristics that are independent of S_i^*.

The influence of work experience on wage rates is captured by a quadratic term. The dataset does not include any questions about the individual's work experience, and hence only potential work experience (defined as $Age - S_i - 6$) would be observable. It is important to note that this measure is also contaminated by the measurement error in schooling reports.

On order to overcome this problem we selected a sample of males aged 35-44. Within this group a linear term would be enough to capture the earnings heterogeneity that comes from work experience. Therefore, manipulating equation [1], under the assumption that $\gamma = 0$ we obtain:

$$\ln(w_i) = \delta_0 + \delta_1 S_i + \delta_2 Age_i + \xi_i \tag{4}$$

$$\xi_i = \eta_i - \alpha v_i + \varepsilon_i \tag{5}$$

where $\delta_1 = \alpha - \beta$ and $\delta_2 = \beta$. It is clear that it would be possible to recover the structural parameters of interest (in particular α) if consistent estimates of δ_1 and δ_2 were available.

Unfortunately, as was discussed above, the OLS estimate of δ_1 in equation [4] is biased and inconsistent. The more the OLS estimate is biased toward zero (the attenuation bias) the greater the variance of the measurement error $\left(\sigma_v^2\right)$ with respect to the variance of true schooling $\left(\sigma_{S^*}^2\right)$. On the other hand, we should remember that a positive correlation

between true schooling and ability - and thus between observed schooling S and unobserved heterogeneity η - would overestimate δ_1.

We used an indicator of whether an Internet connection is available at home as an instrument for the years of schooling of the household head. It seems reasonable to think that this indicator has nothing to do with schooling measurement error. Unfortunately the independence of this instrument with respect to unobserved ability or family background could be debatable. Thus, the instrumental variable estimates could be upwardly biased to some extent. However, the evidence analyzed in previous studies shows that this bias is very small compared to the bias caused by schooling measurement error. Moreover, in the final analysis, the instrumental variable estimates could be seen to correspond to the upper bound of the returns to schooling, while the OLS estimates correspond to the lower bound.

6 Econometric results

6.1 OLS and quantile estimates

Table 2 shows the results based on pooled cross-section OLS and quantile regressions for the period 2001-2005. These results are comparable to previous estimates from Uruguayan data. Notice that these estimates ignore the potential bias introduced by the correlation between, e.g., earnings and either schooling level and family background or the schooling measurement error.

The OLS regression estimates indicate that each additional year of schooling increases the hourly remuneration rate in the private sector by 14 percent (from the estimates 11.9 and 2.2 percent of δ_1 and δ_2 respectively). That number is somewhat higher than the Miles and Rossi (1999) estimates for the period 1986-1997 (10.0 to 12.1 percent) and considerably higher than the OLS estimation by Bucheli and Furtado (2000) for that period (8.6 to 10.5 percent). Casacuberta (2005) uses OLS regressions and founds that the returns to education go from 8 to 10 percent during the nineties and from 10 to 12 in the 2000-2003 period. There are two factors that might also contribute to explaining the difference from these results. First, like those authors, we use a sample of salaried private-sector workers but we restrict the data to males aged 35-44, while they select a sample of males and females aged

18+. Second, their estimate includes controls for firm size and industry, which has the effect of reducing the estimated effect of education. In conclusion, the evidence seems to indicate that there was a moderate increase in the returns to schooling in the 1990s and the first half of the present decade.

We can also compare the quantile regression results to those of Miles and Rossi (1999). They find a U-shaped relationship between education premium and quantiles. The estimates in our paper (see Table 2), however, indicate that there is a steadily increasing pattern in the returns to schooling over the deciles of the empirical distribution. The average return is 10.5 percent (9.1 plus 1.4) in the first decile and 17.8 percent (15.4 plus 2.4) in the ninth decile.

Other considerations arise from the results in Table 2. First, a dummy variable that captures the impact of the 2002 crisis in Uruguay is included. The respective OLS estimate indicates that average wage rates fell considerably, by approximately 30%, between January 2001-September 2002 and October 2002-December 2005. That fall, moreover, is proportionally less acute the higher we move up the wage distribution scale. The fall is a sizeable 40% in the lowest two deciles, it is approximately 25% in the fourth, fifth and sixth deciles, and it fades into insignificance in the four highest deciles. These results indicate that the effect of the crisis was concentrated in the poorer sectors of the population, and therefore it led to an increase in income inequality.

Furthermore, an interaction between years of schooling and the crisis dummy (SDC) is included in order to determine whether the crisis has affected the education premium. The coefficient is not significant in either the mean or the quantiles regressions.

6.2 Instrumental variable estimates

We used an instrumental variable estimation strategy in order to overcome the potential bias of the OLS estimates caused by their measurement error in schooling reports. We used an indicator of whether an Internet connection is available at home as an instrument for the years of schooling of the household head. This variable is clearly independent of the measurement error and it is expected to correlate to true schooling. In particular, an OLS

regression of observed schooling in the proposed instrument performs an R-square of 0.22 and estimates a very significant coefficient of 3.95 with a t-ratio of 27.

The corresponding estimates are presented in Table 3. The standard errors are obtained by using the bootstrap method .(1000 replications). In agreement with previous results, the IV estimates here are much higher than those using OLS techniques. Our results indicate that each year of schooling increases wage rates by 22 percent (19.4 plus 2.9), which is substantially greater than the OLS estimate of 14 percent. A conventional Hausman test of the difference between the OLS estimates and instrumental-variables estimates shows we can reject the hypothesis that these (and the other coefficients) are equal with a χ^2 of 201 (p-value 0.00).

This result can be interpreted as evidence of the presence of measurement error in schooling reports. This estimate is surprisingly higher than expected and a little above international standards (see, e.g., Ashenfelter and Krueger, 1994). However it matches the fact that, in the sample used, the unconditional mean of the wage rate of a 12-year educated worker more is than double that of a 6-year educated worker; and the mean wage rate of a 16-year educated worker is exactly double the average pay of a 12-year educated worker. The IV estimate of the dummy is also very high compared to the figure given by OLS techniques; the mean is 39 percent, which indicates that the effect of the crisis on wage rates was greater than OLS results suggest. On the other hand, the results of the IV quantile regressions differ from traditional-method results because the former indicate that the fall in wage rates is significant in all the decile groups.

IV estimates indicate that wage rates decline approximately 30 percent in the first three deciles, 22 percent in deciles four to eight and 16 percent in the ninth decile. To sum up, there is evidence that wage rates have fallen considerably because of the crisis.

Another difference from the OLS estimation is that the coefficient of the interaction between years of schooling and the crisis dummy is significant and positive; it is in the order of 3.5 percent. Notice, however, that this coefficient is significant in the first three deciles but insignificantly different from zero in the other deciles.

The increase in the returns to schooling caused by the crisis could be interpreted as evidence of greater international mobility of higher-skilled workers as against those who have less education. Labour demand has had to pay more to retain its employees, or - as has been the case in recent years - at least to reduce wages less. Pellegrino and Vigorito (2005) analyzed evidence that indicates that this could be due to the fact that the well-educated are overrepresented in the group of those who have emigrated from Uruguay in recent years.

7 Concluding remarks

In this paper we explore the question of the premium to education by estimating the private returns to education in Montevideo. We propose to overcome the problems of measurement error in reported years of schooling by using an instrumental-variables approach. An indicator of whether an Internet connection is available at home is used as an instrument for the years of schooling of the household head.

The data used in this study are drawn from the Uruguayan Household Survey of 2001 to 2005 (Encuesta de Hogares, Instituto Nacional de Estadística, Uruguay). The sample we use here consists of male household heads aged 35-44 who are private-sector full-time paid workers resident in Montevideo.

The results show that each year of schooling raises wage rates by 22 percent, which is substantially greater than the OLS estimate of 14 percent, and this indicates that the economic returns to schooling in Uruguay may have been underestimated in the past. A conventional Hausman test supports the hypothesis that there is measurement error in schooling reports. This estimate is higher than expected and a little above international standards. However, it matches the fact that, in the sample used, the unconditional mean of the wage rate of a 12-year educated worker is more than double that of worker with 6 years of education; and the mean wage rate of a 16-year educated worker is exactly double the average pay of a 12-year educated worker.

Thus we can conclude that education is a very profitable investment in Uruguay. The evidence also shows that returns to schooling have been increasing over the last two decades, and have increased since the start of the 2002 economic crisis in Uruguay. It is

common knowledge that people from better-educated and wealthier families are disproportionally over-represented at the highest levels of education, and this puts a question mark against the fairness and efficiency of public subsidies for education, in particular for students who go on to the tertiary cycle.

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TABLE 1: DESCRIPTIVE STATISTICS

	The whole sample (N=276346)			The selected sample (N=2671)		
	Median	Mean	S.D.	Median	Mean	S.D.
Wage rate (log)	3.4	3.3	1.0	3.8	3.8	0.8
Years of schooling	7.0	7.5	5.1	11.0	11.0	3.8
Age	35.0	36.9	23.6	40.0	39.6	2.9
Fraction of males		47%	25%		100%	0%
Fraction of Montevideo		54%	50%		100%	0%
Fraction of full-time workers		28%	45%		100%	0%

TABLE 2: OLS and QUANTILE REGRESSIONS

	Mean	*Q10*	*Q20*	*Q30*	*Q40*	*Q50*	*Q60*	*Q70*	*Q80*	*Q90*
S	0.119	0.091	0.099	0.107	0.113	0.111	0.121	0.123	0.137	0.154
	(0.005)	(0.008)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.007)	(0.008)	(0.009)
SxDC	0.001	0.001	0.005	-0.004	-0.003	-0.001	-0.010	-0.004	-0.008	-0.011
	(0.007)	(0.010)	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)	(0.010)	(0.010)	(0.011)
DC	-0.294	-0.394	-0.408	-0.256	-0.248	-0.271	-0.162	-0.201	-0.176	-0.175
	(0.076)	(0.117)	(0.089)	(0.104)	(0.094)	(0.090)	(0.093)	(0.112)	(0.12)	(0.128)
Age	0.022	0.014	0.011	0.021	0.023	0.024	0.025	0.028	0.024	0.024
	(0.004)	(0.007)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)
N	2671	2671	2671	2671	2671	2671	2671	2671	2671	2671
R2 and Pseudo-R2	0.36	0.13	0.16	0.173	0.19	0.20	0.22	0.24	0.26	0.28

Dependent variable is log hourly wages. S is year of Schooling. DC is a dummy that equals 1 if the data is after September 2002. Each equation also includes an intercept term. Numbers in parentheses heteroskedasticity robust standard errors.

TABLE 3: IV-Mean and IV-QUANTILE REGRESSIONS

	Mean	*Q10*	*Q20*	*Q30*	*Q40*	*Q50*	*Q60*	*Q70*	*Q80*	*Q90*
S	0.194	0.142	0.146	0.172	0.195	0.224	0.239	0.243	0.258	0.265
	(0.124)	(0.016)	(0.017)	(0.159)	(0.020)	(0.018)	(0.016)	(0.017)	(0.014)	(0.023)
SxDC	0.035	0.026	0.022	0.017	0.005	-0.005	-0.007	-0.004	0.001	0.001
	(0.016)	(0.010)	(0.010)	(0.009)	(0.011)	(0.010)	(0.009)	(0.011)	(0.010)	(0.014)
DC	-0.398	-0.340	-0.325	-0.319	0.275	-0.282	-0.253	-0.225	-0.264	-0.164
	(0.179)	(0.036)	(0.040)	(0.032)	(0.038)	(0.035)	(0.034)	(0.037)	(0.036)	(0.071)
Age	0.029	-0.007	0.010	0.001	0.006	0.007	0.006	0.014	0.018	0.017
	(0,005)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)	(0.005)	(0.010)
N	2671	2671	2671	2671	2671	2671	2671	2671	2671	2671
$\chi 2(4)$	168									
p-value	0.00									

Dependent variable is log hourly wages. S is year of Schooling. DC is a dummy that equals 1 if the data is after September 2002.
The instrument used is the availability of an internet connection at home.
Each equation also includes an intercept term. Numbers in parentheses are bootstrap (1000 replications) consistent and heteroskedasticity robust standard errors.

Figure 1: Average (log) wage rates
Period: January 2001-December 2005

Figure 2: Average (log) wage rates by years of schooling
Period: January 2001-December 2005