Issues on the return to schooling

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Abstract
In this paper we discuss methodological issues related to the estimation of the return to schooling.
Several alternatives are analysed using an experimental approach as a benchmark.
A novel methodology for estimating shadow amenity prices using choice based conjoint analysis is suggested.
Finally we do estimate the return to schooling using the only data set from Argentina that includes estimates of subject's intelligence.
We find, after many methodological treatments to the data pointed at mimicking experimental conditions, that returns are highly heterogeneous across occupations, sex and labour force participation probabilities.
This is the first paper for Argentina that controls for so many methodological problems simultaneously.

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Resumen

En este trabajo se discuten varios aspectos metodologicos asociados a la estimación de los retornos de la educación.
Varias alternativas son analizadas, tomando al enfoque experimental como marco de referencia.
Una novedosa metodologia para estimar precios sombra de diversas características de los distintos tipos de empleo es sugerida, basada en el método de análisis conjunto basado en la elección.
Finalmente, estimamos los retornos de la educación usando la única base de datos de Argentina que posee un indicador de la inteligencia de las personas.
Luego de varios controles metodológicos que buscan similar condiciones experimentales, encontramos alta heterogeneidad de los retornos entre las ocupaciones, los sexos y las distintas características de los empleos.
Este es el primer paper en Argentina que controla por tantos aspectos metodológicos al mismo tiempo.

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Introduction

Since the seminal work of Mincer (1974) many economist have regressed wages on different sets of attributes including intelligence (Card, 1992; Arias et. al. 2001; Meghir 2005; Plug 2000), behavioural traits (Bowles, 2001; Kwon et. al. 2001), sibling characteristics and birth order (Dancer, et.at 2004), family influences (Becker 1993; Bound et. al. 1986), gender (Oaxaca, 1973;Blau et. al. 1996; del Rio et. al. 2003), race (Neal, 1996; Heckman 1998), socioeconomic influences (Herrnstein et. al. 1994; Psacharopolous, 2002), health status (Schultz, 1985), public vs. private hiring (Tetaz, 2005), and so on.

The explosion of explanatory variables acknowledges at least two main reasons. On the one hand the objective was to find variables influencing wages other than education and job tenure, in order to increase the percentage of variance accounted for by the model. On the other hand, the aim was to control for the effect of relevant variables on the determination of wages so as to estimate the unbiased return to schooling.

This paper focuses on the later, in an attempt to shed light on some methodological issues.

The article is organized in two main sections. In the first we will have some conceptual and theoretical discussion. In the second we will do an empirical exercise. We end with the conclusions.

Conceptual and theoretical issues.

Ideally, if we were interested in estimating the return to schooling we should randomly select potential students into treatment and control groups, giving the treatment group different amounts of schooling than the control.

Then, in the control group we should guarantee that no other training condition is available during the time the subjects normally would have spent studying had they been in the treatment group.

Finally we should estimate the differences in the value of productivity between the two groups during their life cycle.

$$\Delta pQ = \sum_{t=0}^{n} \left(\frac{\Delta Q_t}{(1+i)^t} \right) \qquad (1)$$

Where ΔQ_t stands for the yearly value of productivity of the educated group times the portion of the year they are not studying, minus that of the control.

Assuming that the time spent for the student in the education process is no productive for any other purpose than building human capital (there is no spillovers, and human capital has no other value than its productive one), it follows that expression (1) has a negative value during the first stages of the education process.

Estimating the value of “i” that makes equation (1) equal to zero, produces the private internal rate of return of the investment in education, when the only private cost is foregone earnings.

Notice that if we did compare the productivity of the educated against that of those who went working instead, the resulting would not be the return to schooling but the differential return of that kind of training with regard to the “learning by doing” sort of human capital.

Anyway, unfortunately we hardly have the chance to produce such an experiment, so we have to rely on other methodologies that mimic the experimental approach. Neither we have the possibility to obtain the proper value of productivity, because even though wages are a good proxy, people usually buy "on the job amenities", causing salaries to differ from productivity somehow.

In what follows, we first regard the attempts to obtain cuasi experimental conditions. Later on we will see how the "amenities" problem can be treated.

Natural experiments and instrumental variables

In a famous paper Angrist and Krueger (1991) take advantage of a school attendance regulation that implies that students are bound to start schooling if they are six year old when the academic year begins (September the first), on the one hand, and a mandatory school completion regulation whereby students must be in school until they are sixteen year old, on the other hand.

Both regulations taken together imply that from September the first backwards, the closer the birthday the younger a child starts school. Conversely the younger a child starts school the longer the time she/he spends in the education system before attaining the age of sixteen.

Due to the fact that the month of birth is randomly determined (or at least is orthogonal to the demand of education process) the regulation serves as an experiment, so the return of schooling (actually the differential wage) can be calculated using the Wald estimator; that is: the difference between the incomes of those whose birthday is just after September the first, and the incomes of those born in a date just before, divided by the actual difference in education attainment between both groups.

Nevertheless, Rosenzweig and Wolpin (2000) point out that the subjects were not randomly assigned to the treatment and control groups. Basically, the regulation is responsible for preventing the under sixteen potential droppers, to do so. As a result the Wald estimate is just calculating the differences in the wages of that sub group of students attributable to the extra schooling they were force to take, for the random fate of having been born just before September the first, coupled with the regulation. Then if there were heterogeneous returns to schooling the estimate would not be valid for all students.

In another paper (Tetaz, op. cit.) the number of siblings is used as an instrument, because the author found it correlated with years of schooling attained, yet not correlated with hourly wages. Smoking condition is also suggested as a proper instrument.

As to the former, Rosezweig and Wolpin (op. cit.) criticize the use of that instrument in a previous paper by Butcher and Case (1994) on the grounds that number of children is related to parent's ability, which in turn is somehow inherited by the children. Therefore, the Wald estimate based on the number of siblings instrument would be showing ability bias.

As to the later, some personal traits such us persistence, self steem, strength of will, and many others may be correlated with the decision of smoke, and at the same time influence productivity. If these were the case, again the Wald estimate would be showing the return to schooling for the more productive group.

However, although the author does not provide evidence on the relation between smoking behaviour and personal traits, he shows regressions indicating just a weak relation between the number of siblings and the intelligence of the subjects.

In sum, for any experiment (or instrument) to be valid it has to produce different years of school attainment randomly or at least orthogonally to the distribution of ex ante productivity.

Other Standard approaches

Given the unlikely event of finding an experimental situation, the researchers have had to develop different techniques, in order to make the data sets look as much as possible as if they were coming from experimentation.

Card (2001) is a wonderful review of the latest advances.

One of the main problems to achieve a comparable sample is that wages differ for many reasons other than the differences in school attainment. If the distribution of the variables that influence wages were orthogonal to the different levels of schooling, there should not be a problem because the different groups endowed with different quantity of years of education, would mimic the experimental treatment.

Otherwise, we would not have comparable groups differing just in their level of schooling. On the contrary, some groups would be formed with more productive (regardless educational differences) subjects than others.

Although there are differences in productivity (correlated with schooling decisions) of many kinds, nevertheless the literature shows a bias toward “ability” differences

A common suggestion is to regress wages (usually the logarithm of the hourly wage) on education, including some intelligence quotient.

$$LogW = \alpha + \beta_1 \text{ Years of schooling} + \beta_2 \text{ IQ} \qquad (2)$$

The problem with that strategy is that intelligence changes with schooling (at least until the age of eighteen), and we do not know whether that change is homogeneous across the distribution of initial intelligence.

Moreover, even if it were, there are many other cognitive traits influencing wages other than intelligence. Bowles and Gintis (2001) show that under imperfect information conditions, the market may pay for cognitive traits (they call them, personality traits) that indicate reliability and commitment. In turn, those personality characteristics are probably fostered by education, braking again the cuasi experimental conditions.

Needless to say that, in addition, market structure problems such as barriers to entry into professions, lack of perfect factor mobility, market power, discrimination and many others, may not be orthogonal to the educational attainment process.

A partial solution for the first problem is to estimate simultaneously wages, education and intelligence, as done in Tetaz (op. cit.), but the heterogeneity in the impact of schooling across the different levels of initial intelligence may require some sort of quantil regression analysis (see Arias,et. al. 2001), combined with the multiple equations framework.

On the other hand, any attempt to solve the second, needs to include the consideration of other cognitive traits, besides intelligence.

Finally, the third mentioned kind of problems call for modelling the sorting into different jobs process, or the segmented estimation of the return to schooling for different groups of people, according to the similarity in the market structure conditions, under which they are operating. Instead, dummy variables for the different occupations can be combined with the subjects years of schooling to build interaction terms, as done by Altonji and Pierret (1996)

Selection issues

One of the main problems in the psychology literature (by far the most prolific producer of socio experimental designs) is that subjects are mostly university students that volunteer to participate in the experiments.

A related problem arises when completion of experimental tasks is not mandatory, and some subjects drop the experiment.

Trivial as it may seem, experimental conditions are violated every time the decision to volunteer (or to drop the experiment) is correlated with the process under experimental study. Put it in our current terms, if only the more productive get sorted into the experiment, then the estimated return to schooling would not be that of the less productive people, unless there is no relation between ex ante productivity and the effect of education on wages.

The reader probably has noticed that equation (1) implies a rather wide concept of productivity differentials. Indeed, we postulate that more productive people have an advantage over the less productive all the time, regardless its allocation. As a result, studies that weight wages by the portion of the working time the subjects are unemployed (see Adrogue, 2006) are just estimating the monetary return to schooling, which may not be of much use if non market activities are relevant in the economy.

We know, however that education is likely to influence the allocation of time between market and non market activities, the later including, both homework and leisure.

Unfortunately, we seldom have shadow prices for non market activities. Of course we can assume, following Becker (1990) some process of family time allocation.

In a normative framework, people would allocate their time to the labour market, until an additional unity of time yields less (in terms of the change in the utility it allows) than what can be obtain allocating that unity to family activities (including leisure).

Yet, from a positive point of view, there may exist discontinuities in the utility function, on the one hand, and aggregation issues preventing the family decision mechanisms to behave as a production maximizer, on the other hand. Other discontinuities may emerge, due to labour market regulations, such us the impossibility to change the number of shift hours at will.

Conversely, wage data may suffer the “volunteer bias” described above, every time the decision to participate in the labour market is not orthogonal to the influence of education on incomes.

An interesting solution was put forward by Heckman (1974), Heckman (1979) and Heckman (1990)

The idea is to start by estimating the “volunteering process” (participation decisions in our case), and then estimate the equation of interest (eq. 2), conditional on the participation mechanism.

Of course, participation may not be the only selection bias in a data base. If the number of hours worked is correlated with education, and the productivity of labour market activities is concave in that hours, then we should compare different educated groups, holding constant the number of hours worked.

On the job amenities

We mentioned above the fact that people usually buy on the job amenities, paying for them by means of accepting lower wages, than those that would have corresponded under productivity considerations. Analogously negative amenities are normally traded with higher wages.

Again, if the amenities component of wages were randomly distributed across the schooling distribution, we would just have a noiser estimation, causing not efficient estimates, yet unbiased.

Otherwise, we should add the shadow price of the amenities to the monetary wage on the left side of the regression equation.

In order to estimate those shadow prices, choice based conjoint analysis may be implemented (see Louviere et. al., 2000 and Lancsar et. al., 2007).

Briefly, under that technology subjects are faced with pairs of mix of different attributes of potential jobs, the first being the mix that reflects the current working conditions of a benchmark job (the closer the benchmark to the current conditions, the better), the second a random combination of the same set of attributes. Then the subject is asked to choose between the two sets, or asked whether she would change her current position (in case it is reflected by the first member of the pair), in favour with the alternative mix.

The choice excersise should looks like the following example:

Job A (the benchmark; preferently the current)	**Job B**
Monthly wage = 2000	Monthly wage = 3000
Quality of working activities = Good	Quality of working activities = bad
Quality of working environment = Good	Quality of working environment = Good
Quality of mates = good	Quality of mates = bad
Level of preasure = High	Level of preasure = High
Amenity X = low	Amenity X = high

Every subject is shown many alternative scenarios of working conditions, and asked to produce an election between pairs. Ideally, every subject should face every possible alternative scenario (number of different attribute values powered to the number of attributes), but if we can assume that workers are homogeneous in regard to their amenities considerations, we can replace intra subject's variability with inter subject's one.

As a result, the researcher obtains a vector of differences in attributes between the benchmark and the randomly selected alternative mix on the one hand, and a dummy variable indicating whether the subject preferred the benchmark, on the other.

For example, from the above pair, should the choice is to stay with the benchmark, the following vector emerges:

Choice	Δ wage	Δ QoA	Δ QoWE	Δ QoM	Δ L of P	Δ X
1	-1000	1	0	1	0	-1

Then, coefficients can be estimate by either a logit, a probit or a mixed logit specification (depending on the assumptions in regard to the errors distribution of the random utility model theoretically implied).

Finally, by dividing every coefficient by the corresponding of "Δ wage" we obtain the marginal willingness to pay for a discrete change in each job attribute; it's shadow price.

Notice that a similar strategy can be used in order to estimate shadow wages for those out of the labour force. In that case, we should show the subjects different sets of alternatives, allowing them not to choose between any members of a particular pair, should they prefer to remain out of the labour force, given such a pair of alternatives.

An empirical estimate

The data

To our knowledge, in Argentina there is no data covering cognitive, on the job amenities and earnings aspects at the same time.

To mend that lack of information we run a household survey during the month of April, 2005.

We draw a random sample of 929 subjects covering the area known as “Gran La Plata”, namely the cities of La Plata, Berisso and Ensenada. The area is 600.000 inhabitants located 50 kilometres far from Buenos Aires, the Capital district of Argentina.

To give the readers an idea, La Plata is the Capital of Buenos Aires Province; an administrative city with a big university of almost 100.000 students, whereas Berisso and Ensenada are smaller, but highly industrial.

The survey consisted in 70 questions including a short IQ test, years of education, wage per month; tenure; family background; school characteristics; and many usual questions in the literature.

To obtain a comparable measure, we adjusted the wage reported by the subjects when they were working in the formal sector of the economy, since they usually work 11 month a year but perceive 13 wages a year (due to holydays and complementary annual salary). We did not perform any adjustment to account for pension bonuses, although according to mincer original formulation we should. Briefly, if a worker is promised a pocket wage plus a pension fund when retired, the later is included both in the employer and the employee cost benefit analysis. Unfortunately in Argentina there is a mix pension system, and we have no reason to believe that the pension received by the worker when retired is likely to be related to the tax charged by the government, at all. Therefore we are not able to make proper estimations, but we warn the reader to look at our estimates as low bounds of the proper figure.

The IQ test consisted in eight questions (see Tetaz 2006, for details), but we dropped one due to ambiguity in the legal response (shown to us by an anonymous referee).

With the seven remaining items we performed a factor analysis to find out whether there was a general “latent” factor accounting for the correlations between the items, as described by Spearman (1927). There was no need to rotate the factors since only the first one had a relevant eigenvalue of 1,26 (see Garcia 2004; Cortada de Kohan 1994); the second being of just 0.062.

The results

We begin by trying to tackle the selection problem. In order to do so, we first look at the variables influencing the decision to participate in the labour force. Then we will see if the effect of education on incomes is randomly distributed across those variables.

Age and ability are reasonable candidates, so we regress a labour force participation dummy, on age, it’s squared and IQ. We do it separately for women and men,

since we have reasons to suspect that labor force participation decisions are differently made by both sexes.

```
Probit regression for men                         Number of obs   =        416
                                                  LR chi2(3)      =     117.48
                                                  Prob > chi2     =     0.0000
Log likelihood = -200.41272                       Pseudo R2       =     0.2267

------------------------------------------------------------------------------
       Works |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         Age |   .2351808   .0240948     9.76   0.000     .1879558    .2824058
        Age2 |  -.0025813   .0002728    -9.46   0.000    -.0031159   -.0020467
     factorG |   .2006837   .0935928     2.14   0.032     .0172453    .3841221
       _cons |  -3.952033   .4548645    -8.69   0.000    -4.843551   -3.060515
------------------------------------------------------------------------------
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```
Probit regression  for women                   Number of obs   =        513
                                                  LR chi2(3)      =      75.22
                                                  Prob > chi2     =     0.0000
Log likelihood = -302.59162                       Pseudo R2       =     0.1106

------------------------------------------------------------------------------
       Works |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         Age |   .1508692    .021184     7.12   0.000     .1093493    .1923892
        Age2 |  -.0017893   .0002517    -7.11   0.000    -.0022827    -.001296
     factorG |   .2004469   .0816179     2.46   0.014     .0404786    .3604151
       _cons |  -2.362281   .3969113    -5.95   0.000    -3.140213   -1.584349
------------------------------------------------------------------------------
```

We then predict the working probability of the subjects in our sample using the above regression results and regress the logarithm of the hourly wage on years of schooling and an interaction term of years of schooling times that probability, again for men and women separately.

```
      Source |       SS       df       MS              Number of obs =     247
-------------+------------------------------           F(  2,   244) =   30.35
       Model |  18.8708676     2  9.43543382           Prob > F      =  0.0000
    Residual |  75.8665438   244  .310928458           R-squared     =  0.1992
-------------+------------------------------           Adj R-squared =  0.1926
       Total |  94.7374115   246  .385111429           Root MSE      =  .55761

------------------------------------------------------------------------------
LW men       |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
educ         |  -.0415076   .0142418    -2.91   0.004      -.06956   -.0134551
     edu_pwm |   .0929337   .0136331     6.82   0.000     .0660801    .1197872
       _cons |   1.276904   .1241514    10.29   0.000     1.032358    1.521449
------------------------------------------------------------------------------
```

```
      Source |       SS       df       MS              Number of obs =     265
-------------+------------------------------           F(  2,   262) =   37.59
       Model |  25.6831732     2  12.8415866           Prob > F      =  0.0000
    Residual |  89.5031994   262  .341615265           R-squared     =  0.2230
-------------+------------------------------           Adj R-squared =  0.2170
       Total |  115.186373   264  .436312017           Root MSE      =  .58448
```

```
------------------------------------------------------------------------------
LW women     |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
educ         |  -.0526684    .018678    -2.82   0.005    -.0894465   -.0158902
     edu_pww |   .1379084   .0204076     6.76   0.000     .0977247    .1780921
       _cons |   .9395017   .1411033     6.66   0.000     .6616608    1.217342
```

As the reader can observe there is a significant interaction effect indeed, showing that our sample of working men and women is not random with regard to the effect of years of schooling on wages.

Fortunately, we can control for that effect with the inclusion of the interaction term as an independent variable, simulating by that means the experimental condition.

Sorting and amenity issues

We previously shed light on the fact that imperfect access to segmented labour markets may produce different returns to schooling across occupations, so we proceed by making an interaction term of years of schooling times a dummy variable that take's the value of one if the subject is working in the formal labour market and zero otherwise.

We also build another interaction term that captures the *incremental* return to schooling of those working in jobs reported as "desirables". To do so we take advantage of the fact that we asked subject whether or not they liked their jobs.

Ability issues

We have, as well, an estimate of subject's IQ, so we just introduce our general factor of intelligence, as an independent variable.

As a result we produce the following pair of estimates, for men and women respectively

```
      Source |       SS       df       MS              Number of obs =     246
-------------+------------------------------           F(  7,   238) =   21.54
       Model |  36.7070729     7  5.24386756           Prob > F      =  0.0000
    Residual |  57.9418203   238  .243453026           R-squared     =  0.3878
-------------+------------------------------           Adj R-squared =  0.3698
       Total |  94.6488932   245  .386322013           Root MSE      =  .49341

------------------------------------------------------------------------------
LW men       |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
Years of sch |   -.039538   .0149764    -2.64   0.009    -.0690412   -.0100349
Tenure       |   .0078388   .0029845     2.63   0.009     .0019595    .0137181
Hours worked |  -.0358218   .0115507    -3.10   0.002    -.0585765   -.0130671
     factorG |   .1476027   .0458473     3.22   0.001     .0572843    .2379211
  edu_formal |   .0324865   .0059263     5.48   0.000     .0208118    .0441613
 edu_amenity |    .009019   .0049509     1.82   0.070    -.0007342    .0187722
     edu_pwm |   .0362504   .0149475     2.43   0.016     .0068041    .0656967
       _cons |   1.600282   .1807267     8.85   0.000     1.244254     1.95631
```

Source	SS	df	MS	Number of obs =	258
Model	61.0990356	7	8.72843366	F(7, 250) =	41.94
Residual	52.0321352	250	.208128541	Prob > F =	0.0000
				R-squared =	0.5401
Total	113.131171	257	.440199108	Adj R-squared =	0.5272
				Root MSE =	.45621

LW women	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Years of sch	-.0580267	.0169676	-3.42	0.001	-.0914445	-.024609
Tenure	.0107212	.0028308	3.79	0.000	.0051461	.0162964
Hours worked	-.0850988	.0106352	-8.00	0.000	-.1060448	-.0641528
factorG	.1046253	.045735	2.29	0.023	.0145502	.1947004
edu_formal	.0481521	.0050181	9.60	0.000	.0382688	.0580353
edu_amenity	.0025272	.0044024	0.57	0.566	-.0061434	.0111978
edu_pww	.0666111	.0201199	3.31	0.001	.026985	.1062373
_cons	1.670895	.1555103	10.74	0.000	1.364617	1.977172

Interestingly, there seems to be many different returns to schooling according to the extent to which the job is desirable (for men) and it is located in the formal sector(for both).

In addition, we find that the return increases with the probability of being in the labour force, indicating that the studies that do not control for that selection issue may be showing just the return for those working.

There is also a different impact of those variables between women and men. The effect of education on wages is bigger to the former as usually found in the literature.

Intelligence, plays also a key role in wage levels. To give the reader an idea, since one standard deviation in the general factor of intelligence equals 0,78 so one standard deviation in general intelligence generates a 14,10% increase in men wages and a 11,79% in women

The reader must bear in mind that our estimates do not show actual rates of return in the sense previously defined in this paper, but wage differentials due to schooling, which is not the same.

Moreover the previous estimates suffer the lack of a proper data base.

Ideally, we would have liked to have a choice based conjoint analysis, to estimate the shadow amenity prices, as well as a broader data set in order to have more variability

Challenging as it may be, however, that is out of the possibilities of this paper.

Final comments

We discussed in this paper different approaches to estimate the return to schooling.

The proper methodology would imply the realization of an experiment whereby some randomly selected subjects are endowed with a unit of education, whereas a control group of equally selected individuals is not given any sort of training at all.

Lacking that possibility, any other methodology should try to mimic the experimental design.

To do so, ability and selection issues must be taken into account, as well as considerations regarding on the job amenities.

In the final section of this paper we tried to mend the lack of a proper experiment, by proposing different methodological solutions to the problems mentioned above.

We, indeed find that the effect of education on wages is not orthogonal to the distribution of people, neither among occupations, nor between the labour and non labour forces.

As a result an average rate of return of education may not be informative for policy purposes.

More research is obviously needed, and new data bases that carefully measure subjects and jobs heterogeneity are welcome.

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