THE EFFECTS OF INDIVIDUAL CHARACTERISTICS ON THE DISTRIBUTION OF COLLEGE PERFORMANCE

WALTER SOSA ESCUDERO, PAULA INES GIOVAGNOLI AND ALBERTO PORTO

RESUMEN

Las interacciones entre los determinantes observables e inobservables del éxito educativo implican que los primeros tienen un efecto heterogéneo en el rendimiento. Para cuantificar estas interacciones, se estima un modelo de regresion por cuantiles utilizando microdatos de universidades públicas argentinas. Los resultados muestran que los factores que contribuyen positivamente al rendimiento son mayores en las colas inferiores de la distribución. Políticas que mejoran el rendimiento de quienes se encuentran en la parte inferior de la distribución condicional tienen un efecto dual de incrementar los rendimientos absolutos y de reducir las disparidades debido a un mayor efecto en este grupo.

Clasificación JEL: I21

Palabras Clave: Argentina, rendimiento educativo, educación universitaria, regresión por cuantiles.

ABSTRACT

Interactions between observed and unobserved determinants of educational success imply that the former have a heterogeneous effect on performance. To quantify these interactions, a quantile regression model is estimated using a database of students at public universities in Argentina. The empirical results show that all factors which contribute positively to performance are stronger in the lower end of the distribution. Hence, policies that enhance the possibilities of students in this part of the conditional distribution have the dual effect of increasing absolute performance and reducing disparities due to their stronger effect in this group of students.

JEL Classification: I21

Keywords: Argentina, educational performance, higher education, quantile regression.

THE EFFECTS OF INDIVIDUAL CHARACTERISTICS ON THE DISTRIBUTION OF COLLEGE PERFORMANCE [1]

WALTER SOSA ESCUDERO, PAULA INES GIOVAGNOLI AND ALBERTO PORTO [2]

I.   Introduction

Considerable space has been awarded in the social and human sciences to the question of how individual characteristics impact on educational performance. A quantification of how student-specific factors affect educational success is crucial to explain disparities in educational achievements, and to design and evaluate specific actions aimed at promoting upward social mobility. This requires accurate empirical models that link educational performance to its observable determinants.

As has been well documented, mostly due to the inherent complexity of the problem, available models are still far from this goal, which is usually reflected in their very poor goodness-of-fit performance. For example, Betts and Morell (1999) in a related study for the University of California at San Diego, obtain R^2 coefficients of around 0.15, using a rich dataset of 5,623 students[3]. This means that even after conditioning on many observable aspects that determine success, individuals still differ substantially due to unobserved factors. Consequently, the correct way to assess the effect of an observable variable on performance is to think about how changes in this specific factor affect the *conditional distribution* of performances.

[2] Walter Sosa Escudero: Universidad de San Andrés. Paula Inés Giovagnoli: London School of Economics and Universidad Nacional de La Plata. Alberto Porto: Universidad Nacional de La Plata. Corresponding author: Paula Giovagnoli, London School of Economics and Political Science, Houghton Street, Tower Two Building, 5th Foor, Room V512. London WC2A 2AE, United Kingdom, e-mail: p.i.giovagnoli@lse.ac.uk.
[3] The explanatory power of the models doubles when they incorporate the previous performance of students in their estimations. The importance of considering education as a cumulative process is based on Hanushek (1986) who remarks that '.. current inputs are frequently very inaccurate indicators of past inputs………' (p. 1156).

As a simple example consider the effect of father's education. The distribution of performances conditional on observed factors, including father's education, still presents substantial variability due to the non-trivial role played by unobservables, hence, even within a group of individuals with the same observed characteristics, we will find students with bad, regular, or good educational performance. It is natural to expect that the whole conditional distribution of performances gets shifted to the right when, other things equal, we consider students with better educated fathers. In the extreme case where additional father's education shifts the whole conditional distribution to the right without altering its shape, the effect of increasing father's education on the *mean* performance captures everything there is to know. In such a context, and under some simplifying assumptions, a standard regression model gives the desired answer: the coefficient of fathers's education in a linear regression captures the effect on expected performance and, under these circumstances, on performance in general. This situation naturally arises when father's education is independent of non-observables in the determination of performances, hence, movements in father's education imply pure location shifts of the conditional distribution of performances. But given the non-trivial role played by unobservables in these models, we cannot discard the possibility that movements in father's education interact with factors not included in the model in a non-obvious way. It might be the case that father's education play a more important role in children less inclined towards study, and a mild effect on those more motivated. In this case, the 'mean effect' of father's education is positive but does not represent anybody in the population: it overestimates the effect on individuals with high propensity towards study, and underestimates the situation of the less motivated students.

A second example, derived from the empirical results of this paper, is the following. Consider the effect of age on college performance. The group of older students may be a mix of more focused and mature individuals together with badly motivated students who advance slowly in the educational process. Unless we can control for abstract, difficult to measure factors like 'focus', 'maturity' and 'motivation', other things equal, the cluster of older students might perform on average like the group of younger students, even though the former is certainly more disperse in their performance. In this case the conclusion that 'on average' age does not have an effect on performance might

lead careless observers to the wrong conclusion that age does not have any effect, ignoring its impact on the dispersion.

The main goal of this paper is to measure the effect of observable individual characteristics on the whole conditional distribution of performances using recent *quantile regression* methods. We are not trying to isolate the causal effects of the observable variables included in the model, but instead our focus is on the differences between the incremental effects of the variables at the different quantiles of the conditional performance distribution. There are three main reasons why the quantile regression approach is relevant. First, it complements standard 'educational production function' studies by exploring effects beyond those on the conditional mean. This is important since educational policies are usually expected to have an impact on those students who face relatively more difficulties, so extrapolating the effect of the average individual may induce considerable biases in the assessment of such policies.

Second, mean effects are seldom informative about the *distributive* impact of policies. The presence of heterogeneous effects suggests that changes in specific characteristics may have the effect of improving everyone's performance but also of altering the shape of the distribution of these performances. Quantile methods provide an informative picture of these distributive effects. This is a particularly relevant issue since education is explicitly seen by many social actors as an active equalizing policy[4]. For example, and as a preview of some empirical results, having attended a private

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[4] The 1994 reform to the Argentine Constitution explicitly states as an obligation of the Congress to 'pass laws that ensure equality of opportunities and possibilities without any discrimination; and guarantee principles of free-tuition and equity in public education as well as the national university's autonomy (inc.19)'. Moreover, among the objectives of the Higher Education Law (24521/95 - Article 4th) are 'To deepen the process of democratization of Higher Education, to contribute to an equal distribution of knowledge and to ensure the equality of opportunities' (inc. e). The same article sets forth as another objective those already provided by the Federal Educational Law (No 24195/93, 5th Article) 'the achieving of effective equality of opportunities and possibilities for all inhabitants and the rejection of any kind of discrimination' (inc. f) and 'Equality through the fair distribution of educational services in order to achieve the best quality and equivalent results deriving from a heterogeneous population' (inc.g). In the same vein, the Financial Education Law (26075/05) establishes an increase in the allocation of fiscal resources toward the education system up to 6% of the total GDP by 2010. Its objective is clearly stated in the first article '..to guarantee equality of opportunities of learning' (Art.1st).

secondary school (as opposed to public) has a positive effect on performance for individuals around the center of the distribution of their unobservable factors, and no effect for those extremely good or bad. Then, having attended a private secondary school makes the distribution of performances more *asymmetric*, a subtle but relevant effect improperly summarized by the 'average' effect.

Third, distributive results become crucial when the *screening* perspective of schooling is emphasized. In this context, what matters is the capacity of the educational system to provide information about the relative abilities of individuals, and hence, as stressed by Hanushek in his classic survey '...more attention should be directed towards the distribution of observed educational outcomes (instead of simply the means)...' Hanushek (1986, pp. 1153).

The analysis of the relationship between educational outcomes and observed factors has been investigated more intensively at the elementary and secondary levels, leaving ample room for contributions aimed at the higher education level. The empirical application of our paper exploits a comprehensive census data set that covers all students attending public universities in Argentina in 1994. Public higher education in Argentina has been operated as a free and unrestricted access system -in general without entrance examinations- during most of the last twenty years, providing a rather unique source of sampling variability. Students entering university come from diverse socio-economic backgrounds. Additionally, in some popular degree programs like Accountancy or Law, university rules are very flexible and leave the student's progress up to themselves. This results in very different performances among students of the same cohort, adding greater value to our data set. To the best of our knowledge, this is the first paper that takes advantages of these particular features.

There is some relevant prior work to our study. Eide and Showalter (1998) and Levin (2001) use quantile methods to study how school characteristics affect performance. Betts and Morell (1999) conduct a comprehensive analysis of the determinants of college performance using a large sample of University of California at San Diego students. A relevant conclusion of their paper is that '...variations in family background and in the socio-economic environment of the school play far more crucial roles in determining student outcomes in university than do variations in school resources, which is in line with empirical results that go back to the 1966 Coleman Report. Consequently, and

in light of these results, we emphasize the use of quantile methods to study how *individual* characteristics impact on performance. As mentioned before, the literature on higher education and performance is relatively scarce as compared to that related to elementary and secondary education; a representative study of this literature is Naylor and Smith (2004), who study the determinants of college performance for the United Kingdom and Di Gresia et. al. (2007), Porto (ed.) (2007) for the case of Argentina.

The rest of the paper is organized as follows. The next section discusses the econometric strategy used to recover the effects of observed variables on conditional distributions, while linking this study to previous literature on the subject. Section III presents the data set used in the empirical part and details the particular aspects of the Argentinean higher education system which are relevant for the purposes of this paper. Section IV presents the econometric results, and Section V concludes.

II. Exploring distributive effects through quantile regressions

As mentioned in the Introduction, non-trivial distributive effects of observed factors arise when they interact with non-observables. This section presents a simple structure for these interactions and proposes the use of quantile regressions to model them.

A. Interactions between observed and unobserved factors

The educational production function approach, originated in the famous 'Coleman Report' and reviewed extensively by Hanushek (1986), models educational performance as the outcome of transforming 'inputs' into educational 'outputs' in a production function fashion[5]. A stringent empirical limitation of these models is that the vector of inputs includes a myriad of unobserved individual specific factors which may play a non-trivial role. To the point, in his landmark paper Hanushek (1979) states that '...the most consistent and obvious divergence of the empirical models from the conceptual models is the lack of measurements for innate abilities'. In educational production functions, these abilities play a role similar to that

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[5] The importance of understanding education as a production process had already been put forward by Olivera in 1964, stating that 'education, in some sense, is a branch of production. As well as in any other industry, (education) utilizes material and human resources and labor and capital in order to obtain some outputs' (pp.103 see also, Olivera (1967) and Araoz (1968)).

played by 'entrepreneurial factors' in standard micro-theory production functions, in the sense that they represent unobserved factors that imply different profits for different firms (individuals, in the case of education) and that may alter the way observed factors affect production.

Consider a simple, individual specific, production function

$$y_i = g_i(x) \tag{1}$$

that represents the maximum educational outcome y that an individual i may produce with inputs x. In general this function is not homogeneous of degree one since each person has its own set of fixed 'innate abilities'. As clearly stressed in the standard microeconomic theory (i.e., Mas Collel, et al., 1995, pp. 134-35), production functions reflect technologies, not limits on resources, hence the individual specific production function is better represented by

$$y_i = g(x, u_i) \tag{2}$$

where u represents unobserved factors that once fixed at a particular level describe how x is transformed into y for a particular person.

As it is well known in the literature, u is far from playing a minor role in explaining educational disparities. Even when the dimension of x is large so as to include a multitude of individual and institution specific factors, u still contains abundant unobserved information about the psychological and motivational characteristics that make individuals differ in their performance[6]. Hence it is risky to proceed by making strong assumptions about the role played by u in the production process.

In particular, we are concerned with the possible interactions between unobserved and observed factors. This is a question related to the specific form of $g(x,u)$. Using a translog specification, Figlio (1999) explores interactions among *observed* factors by testing the statistical significance of interactive terms. But if interest lies in exploring interactions between observed and *unobserved* factors we cannot rely on such a strategy.

B. The quantile regression approach

Consider the following general, possibly non-separable, production function:

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[6] This is typically reflected in the low goodness-of-fit performance of these models, even when large scale data bases or flexible forms are used (Betts and Morell (1999), among others).

$$y = g(x,u) \tag{3}$$

and, to simplify notation, consider the case where x is a single observed explanatory factor. Our interest is in exploring whether $\partial y/\partial x$ varies with different levels of u, and 'separability' or 'no-interaction' means that this derivative is constant across the different levels of u. Since u is not observed by the analyst it is awkward to speak about its absolute levels. Instead, it seems more convenient to consider a standardized relative notion, like its quantiles, that is, levels of u that are deemed as 'high' based on the (relative) notion that a large proportion of its possible values lie below them[7].

In this context the starting point is how much of y can be produced when u is set at its τ-th conditional quantile given x, that is,

$$g(x,Q_{u|x}(\tau)) \tag{4}$$

where the notation $Q_{z|x}(\tau)$ stands for the τ-th quantile of the distribution of a random variable z conditional on x[8]. If, as is standard for any production function, we assume that $g(x,u)$ is monotonic in u when x is fixed, and since quantiles are equivariant under monotonic transformations (i.e., $Q_{h(z)}(\tau)=h(Q_z(\tau))$ for any monotone function $h(.)$), then

$$g(x,Q_{u|x}(\tau)) = Q_{g|x}(g(x,u))(\tau) = Q_{y|x}(\tau) \tag{5}$$

Hence how much can be produced when u is set at any relative level measured by its conditional quantiles coincides with the τ-th conditional quantile of performances. In the simple case where x is a single production factor, in the space (y,x) this corresponds to a *family* of production functions indexed by the conditional quantiles of u. Figure 1 illustrates this point where each curve corresponds to $g(x,Q_{u|x}(\tau))$ for increasing levels of τ.

Consequently, our measures of interest are the partial derivatives of these production functions for different relative levels of u, $\partial Q_{y|x}(\tau)/\partial x$. Quantile regression models are specifically designed to estimate these derivatives.

Using the chain rule in (5)

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[7] Roemer (1998, pp.10) adopts a similar relative characterization when he uses *centiles* to measure effort.

[8] This argument follows Chesher (2003) who studies the identification of general non-separable functions.

$$\frac{\partial Q_{y|x}(\tau)}{\partial x} = \frac{\partial g(x,u)}{\partial x} + \frac{\partial g(x,u)}{\partial u} \frac{\partial Q_{u|x}}{\partial x} \tag{6}$$

In this context 'separability' means that $\partial g(x,u)/\partial x$ does not depend on the levels of u and that $\partial Q_{u|x}/\partial x$ is zero, that is, u is independent of x.

As an illustration consider the linear case

$$y = \delta_0 + \beta_1 x + u, \tag{7}$$

so

$$Q_{y|x}(\tau) = \delta_0 + \beta_1 x + Q_{u|x}(\tau) \tag{8}$$

If u is independent of x

$$\frac{\partial Q_{y|x}(\tau)}{\partial x} = \frac{\partial y}{\partial x} = \beta_1, \tag{9}$$

a constant, since there is no explicit interaction between x and u and since u and x are independent.

The simplest specification that allows for these type of interactive effects is provided by the standard linear quantile regression model

$$g(x,Q_{u|x}(\tau)) = Q_{y|x}(\tau) = \alpha(\tau) + \beta(\tau)x \tag{10}$$

where $\beta(\tau)$ is any function. This implies that for any fixed τ, $g(x,Q_{u|x}(\tau))$ is a linear function with slope $\beta(\tau)$. Interactions arise due to the fact that for any given x the slope of these lines is allowed to vary across the conditional quantiles of u. The null hypothesis of 'no-interaction' corresponds to the case where all slopes are equal, $H_0{:}\beta(\tau) = \beta_0$.

Based on a sample (x_i,y_i), $i=1,\ldots,n$ of independent, though not necessarily identically distributed observations, coefficients of this model are estimated for several quantiles using the standard Koenker and Bassett (1978) estimator that solves:

$$\hat{\beta}(\tau) = \operatorname{argmin} \sum_{i=1}^{n} \rho_\tau(y_i - x_i' b(\tau)), \tag{11}$$

$\rho_\tau(z) \equiv z\,(\tau - I\,(z{<}0)), \tau \in (0,1)$. Basic inference, like individual significance tests and confidence intervals, is handled as follows. We estimate the vector of unknown coefficients for a grid of M equally spaced quantiles τ_m, $m = 1,\ldots,M$.

Let $\hat{\beta}(\tau_m)$ be each of these vectors of coefficients, and let $\beta(\tau_m)$ be their population counterparts. Collect all coefficients for all chosen quantiles as $\hat{\beta} \equiv (\hat{\beta}(\tau_1)' \cdots \hat{\beta}(\tau_M)')'$ and $\beta \equiv (\beta(\tau_1)' \cdots \beta(\tau_M)')'$. Under the assumption of a random and independent sample (not necessarily identically distributed) and under standard regularity conditions,

$$\sqrt{n}(\hat{\beta}_n - \beta_0) \xrightarrow{d} N(0, V_n) \tag{12}$$

where V_n is an $MK \times MK$ block diagonal matrix with blocks:

$$V_n(\tau_m, \tau_j) = [\tau_m \wedge \tau_j - \tau_m \tau_j] H_n(\tau_m)^{-1} J_n H_n(\tau_j)^{-1} \tag{13}$$

with

$$J_n = (1/n) \sum_{i=1}^{n} x_i x_i' \tag{14}$$

$$H_n(\tau) = \lim_{n \to \infty} \sum_{i=1}^{n} x_i x_i' f_i(F_i^{-1}(\tau)) \tag{15}$$

and f_i stands for the conditional density of y_i. $H_n(\tau)$ is estimated using the Koenker-Hendricks procedure. We refer to Koenker (2005) for further details.

Linear hypothesis of the type $H_0 : R\beta_0 - r = 0$, where R is a $q \times MK$ matrix and r a q vector, can be evaluated through the statistic:

$$T_n = n(R\hat{\beta} - r)'[R V_n^{-1} R']^{-1}(R\hat{\beta} - r) \tag{16}$$

which is distributed as $\chi^2(q)$ asymptotically under H_0, where q is the rank of R. This allows several configurations like individual or joint significance of variables, or the 'homogeneity' assumption that coefficients are equal across quantiles.

Consider the homogeneity assumption $H_0 : \beta(\tau) = \beta_0, \tau \in (0,1)$ where all slopes are equal across *all* quantiles. The previous approach handles this hypothesis through evaluating it at a discrete grid of selected quantiles. Koenker and Xiao (2002) propose appropriate tests for this hypothesis along a continuous range for τ. The homogeneity null is usually referred to as the 'pure location shift' hypothesis, since under it variables have the effect of shifting the whole conditional distribution without altering its shape. A less drastic hypothesis is the pure 'location-scale' hypothesis which implies a particular form of heterogeneity where variables shift the conditional

distribution while altering its scale in a simple 'heteroscedastic' fashion. We implement both tests, and refer to Koenker and Xiao (2002) for technical details.

III. Data and main features of the higher education system in Argentina

We base our study on the CEUN (Censo de Estudiantes de Universidades Nacionales), a national census data set that covers all college students enrolled at the 31 national universities in Argentina in October 1994, amounting to approximately 615,000 students. This database includes detailed information on several personal and household socio-economic characteristics, as well as college performance for each student in the sample.

Because of its distinguishable institutional features, the sampling variation in our data is ample, offering a rather unique empirical opportunity to study the determinants of college success. Specifically, the system of public universities in Argentina has a long tradition of promoting equality of opportunities by providing free and unrestricted access to higher education. Free-tuition remained even after the Higher Education Law was passed in 1995, which provides universities with full autonomy over their administration, internal resource allocation, staff management, and student access. According to this Law, it is up to the universities to decide whether or not they want to charge fees[9]. Nevertheless, the great majority of universities do not charge tuition and, in general, there are no limiting entrance examinations.

Our data is also less vulnerable to the negative effects of the selection mechanisms present in most universities, specially those in the American or British systems where strong competitive schemes determine access. For instance, in the US or the UK, students must achieve a minimum score at secondary education level in order to apply to a specific university. This restriction influences the allocation of students to particular universities, biasing correlations between educational performance and students in such samples.

Other countries in Latin America or Europe (for example, Germany) also promote free access by keeping tuition levels at relatively low or zero cost, but the case of Argentina is important since tuition-free is, in general,

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[9] Higher Education Law, Chapter IV, Section 1, Article 50.

simultaneously combined with free entrance, independent of previous student performance in secondary school or pre-examinations.

Compared to other countries, higher education coverage in Argentina ranks among the highest. According to the official Permanent Household Survey from May 2003, 65% of young people aged 18-29 years old who completed secondary school started university, and 20% of them are in the lowest quintile of the equivalized household income distribution[10] compared with 32% in the highest quintile, showing that beneficiaries of public university education come from families located in different parts of the income distribution.[11]

Our dataset provides evidence that students attending higher education come from a diverse socio-economic background and constitute a heterogeneous group. Moreover, additional statistics for a subgroup of our data show that poor people do not only start university but they also obtain a degree- albeit with lower chances than those who come from the richer families. For instance, following a cohort of Accountancy students at National University of Rosario since 1991 up to 2001, Giovagnoli (2005) noticed that 20.4% of those who graduated had fathers with primary education or less.

An additional characteristic that makes Argentina's public higher education system an attractive case is that students in most programs face highly flexible schedules and mild requisites that allow them to proceed at their own pace. Hence a cohort of students could advance very dissimilarly along its academic path without being penalized, leaving ample room for individual characteristics to play a role as determinants of performance. As we will show later, data confirms this pattern. Specifically, for reasons explained below, focusing on a cohort of students who started university in 1991 and measuring their performance by 1994, we observe high variation.

The choice of a particular measure of performance is a delicate issue subject to much debate. Some authors draw on measures such as GPA's (Betts and Morrell, 1999), the Graduate Record Examination (GRE) (McGuckin and

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[10] Equivalized income takes into account the fact that food needs are different across age groups - leading to adjustments for adult equivalent scales - and that there are household economies of scale.

[11] Gonzalez Rozada and Menendez (2004) suggest that the opposite conclusion holds. They conclude that poor students tend to be excluded from higher education and hence do not obtain the benefits of free access. Their results, however, arise from comparing individuals attending higher education versus those in the relevant age group who do not attend college, regardless of their secondary school status (ibid, page 4).

Winkler (1979)) or the estimation of potential incomes (Card and Krueger (1996)), to give a few examples. These measures are unavailable in the CEUN data set. Nevertheless, there are no theoretical or empirical reasons to consider that one indicator dominates the others, in fact, there is a vast literature revising the weaknesses and the strengths, supporting the use of different measures - for a rich and extensive discussion on the issue see Hanushek (1979, 1986). In this paper we measure performance as the number of courses passed from the beginning of the program (as we will be working with the cohort of students enrolled in 1991 observed in 1994, we will measure number of courses passed after 4 years of study). In the context of understanding education as a production process already discussed in Section II this is a measure of average productivity. Thus, a student who passes more courses per year demonstrates greater productivity - i.e. has a better performance - than another one who contemporaneously started university and passed less courses. The former student will be able to incorporate human capital in a shorter period of time leading to earning incomes at an earlier point in the life-cycle.

With respect to the choice of explanatory variables, the underlying theory is not explicit about any particular choice, hence data availability has played an important role in this decision. Following previous research (Hanushek (1979, 1986), Naylor and Smith (2004) and Betts and Morell (1999)), we will consider the inclusion of particular variables which can be grouped into four main types: (i) the student's demographic variables (gender, age); (ii) the student's family background (parent's education); (iii) the student's chosen factors such as the decision to work or not, city of residence/or commuting and marital status and (iv) type of school that the student attended prior to enrolling in university (public or private secondary school, type of orientation - commercial or others[12]).

Our empirical analysis is focused on the two most popular programs, Law and Accountancy, at the four largest universities: University of Buenos Aires (UBA), National University of Cordoba (UNC), National University of Rosario (UNR) and National University of La Plata (UNLP). The choice of

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[12] Commercial/Administrative orientation includes basic theoretical and practical concepts about Business Administration, Accountancy and Economics. Other orientations are: (a) Humanistic, which includes concepts about different areas, specially designed to continue tertiary/university levels and (b) Technical orientation which is focused on the production process in different sectors of the economy, and much less popular than the other two.

this particular sub-sample is based on the usual trade-off between increased information and heterogeneity: more programs and universities provide more sample points at the potential cost of introducing heterogeneities between schools and programs that may obscure the goals of our analysis. Students at these four universities concentrate more than 50% of total enrollment at national universities in the country and, out of these, approximately 30% study Accountancy or Law (among 900 other career options).

Interestingly, these programs are quite homogeneous among national universities of the country because an important part of their syllabi is related to national laws and codes, and their professional practice is subject to strict regulations[13]. This allows us to pool observations from different universities and increase precision without introducing heterogeneities at university level[14].

From the total number of individuals studying Accountancy and Law in the 1994 Census, we focused on students who enrolled during 1991, who are approximately 8.000. As these programs have a nominal length of at least five or six years, the very good students of this cohort were in their fourth year at the time of the census. More recent cohorts (those who entered after 1991) passed less courses at the time of the census, hence their measure of performance is a less precise indicator. In the extreme case, the 1994 cohort has only passed a few number of courses, thus the average number of courses passed may be a very poor predictor of overall performance. On the other hand, older cohorts are not correctly represented since their best students may have finished college in the expected five years of study and are naturally not present at the moment the census was conducted.

Table 1 shows descriptions and summary statistics for the variables included in our dataset. The performance indicator reveals that after four years students in Accountancy programs passed, on average, 12.13 courses, hence

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[13]Unlike the US system, the professional practice of lawyers and accountants in Argentina requires an undergraduate degree in Law or Accountancy, respectively. For example, to become a professional accountant a student must obtain an undergraduate degree in Accountancy and then obtain a professional license in the province where she/he is interested to practice her/his profession. The license is awarded automatically to every graduate, without exams, since it is understood that the professional evaluation has already taken place at the University. Accountancy norms are quite homogeneous across different provinces. The case of lawyers is similar.

[14]When we analyzed the structure and syllabi for each program among universities for 1991 cohorts, UNLP seems to be less flexible (especially in Accountancy) than the other Universities. UNLP also has a greater number of missing data in the data set.

the average productivity is around three courses passed per year. Note that in the case of Law, the nominal duration of the program is one year more than Accountancy, while the number of courses is similar. Then, by 1994 Law students should have passed fewer exams than those in Accountancy.

While the same proportion of males and females attend Accountancy, females are relatively overrepresented in the Law program (59%). The latter sample has slightly older and non-single students, and 56% of the students come from a public secondary school. In Law there is a significant smaller proportion of students than in Accountancy who previously attended a secondary school with commercial orientation compared with those who attended a different secondary school orientation (33% versus 65%).

Labor market variables suggest a very dissimilar composition in each program related to the kind of job students have. Although around 35% of both accounting and law students said they did not have a job by 1994, working groups are different between the programs. While 41% of accounting students have a job related to their careers, only 22% of Law students have a job linked to their profession.

Regarding the characteristics of student's fathers, in Accountancy, they have, on average, 11 years of formal education, which corresponds to incomplete secondary school. Fathers of students in Law are slightly more educated. Finally, the proportion of students in each university highlights the relevance of UBA in the total sample - 56% (49%) of Law (Accountancy) students are from UBA, with UNC being the second largest in terms of the students in the sample.

IV. Estimation results

We have estimated a basic linear quantile regression specification using the log of performances as the dependent variable, for Accountancy and Law students respectively, pooling the information from the four universities considered, and including dummy variables by universities.

Tables 2 a) and b) present estimation results for Accountancy and Law separately. The first five columns of each table present point estimates of the coefficients of the linear quantile regression model of (log) performances for quantiles 0.1, 0.25, 0.5, 0.75 and 0.9. The sixth column presents standard OLS estimates which measure mean effects. The last two columns present the Koenker-Xiao statistics for the null hypothesis that the effect of each variable

is a location shift and a location-scale shift, respectively. In the bottom of these two columns we present the test statistics of the global hypothesis of location shift and location-scale shift. These tests strongly reject the null of homogeneity or pure location effects, stressing our initial point that the effect of observed factors is heterogeneous across the quantiles of unobserved factors, suggesting the presence of non-trivial interactions, in the sense discussed in section II.

Figures 2a) and 2b) present these results graphically, for Accountancy and Law, respectively. Each small picture presents the effect of each explanatory variable on the τ-th quantile of the conditional distribution for a finer grid of quantiles (τ=0.1,0.11,…,0.89,0.9). The solid line shows the effect at each quantile and the shaded area represents a 90% confidence interval. The dotted horizontal line represents the OLS estimation. When relevant, the solid horizontal line simply indicates zero.

Now we turn to the analysis of the effect of individual factors. We will start by commenting results for Accountancy and then highlight differences and similarities with respect to Law. The gender dummy has a negative and significant effect in the mean OLS based model for Accountancy, suggesting that the expected performance of males is around 6% lower than that of females. Nevertheless, quantile regression results reveal that the effect is stronger in the lower levels of the conditional distributions, decreasing in absolute values and becoming statistically insignificant at the upper level. Figure 3 illustrates this point by showing the conditional densities of performances of Accountancy students, for males and females, with all the remaining covariates set at their mean levels.[15] Even though the effect is in general mild, the estimated densities show that the conditional distribution of males' performances have a larger left tail, so gender differences appear mostly in this range and not among those with higher performance. The case of Law students, illustrated graphically in Figure 4, is slightly different, since the gender dummy is significant only in the middle part of the conditional distribution and insignificant in the extremes, consequently, the conditional distribution of performance for females is skewed to the right as compared to that of males. Though the effect is mild, it appears clearly in Figure 4.

An important issue is the effect of having private versus public secondary education. The positive OLS based effect is actually a consequence of a

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[15] The Appendix describes the procedure used to estimate these densities.

positive and significant effect in the center of the conditional distribution of performances, in spite of being insignificant in the extremes. There are several intuitions behind this result. Public secondary schools in Argentina are, overall, perceived to be of lower quality than private ones since they usually receive students with less favorable socioeconomic backgrounds, except for a few which are very traditional and manage to attract the very best students. Consequently, the fact that effects are nil in the extremes and positive in the center is compatible with the idea that once in college students from public secondary schools have a markedly negative asymmetric distribution of performances, most of them in the lowest tail of the distribution and relatively few at the top. The opposite results appear in the case of those with private education: most students have a good performance and relatively few of them have extremely bad performances. In either case the very good students, in terms of their performances, do not seem to have benefitted from having attended one type of school or the other, and the same happens in the other extreme. This result is illustrated graphically in Figure 3, where the conditional densities of performances are plotted for students with private and public secondary education. The central part of the conditional distribution for those with private secondary school education appears shifted to the right, with the extremes unaltered, compared with those students with public secondary school background, compatible with positive effects in the middle and nil effects in the extreme. The case of Law students is different since private education has a strong effect in the bottom of the conditional distribution, decreasing monotonically and having a rather constant effect beyond the quantile 0.4.

Regarding parental education, as expected, the mean effect is positive, implying that students with better parental background are expected to perform better. Quantile regression results provide relevant additional information suggesting that this effect is clearly heterogeneous, much stronger in the bottom of the distribution. A similar effect is found for the case of Law students. This is consistent with a decreasing returns effect (semi-elasticities, in our case) where if we start at the bottom of the distribution of unobserved factors and measure the effect of increased family background, we should expect it to be positive but marginally decreasing as we move progressively towards groups of individuals more favored in their unobserved factors. Graphically, Figures 3 and 4 plot the conditional densities for individuals with parents with 7 and 18 years of education. The distribution of performances of

students with more educated parents is shifted to the right and more skewed to the left, consistent with the effect of parental education being positive but decreasing across the quantiles.

Age effects are interesting. OLS estimations are insignificant for both accountants and lawyers, suggesting that age has no effect on the conditional mean of performances. Nevertheless, the age effect by quantiles ranges monotonically from being significantly negative in the lower levels to slightly significant and *positive* in the upper quantiles; a very similar and stronger effect is found for the case of lawyers. This seems to be indicative of a pure *scale* effect where, other things equal, classes with older students are more disperse in the sense that age plays a positive role for those in the upper tail of the distribution of non-observables and a negative one for those conditionally in the bottom. This is consistent with the intuition that good but otherwise older students may be more focused and mature about what they expect from their education (the positive effect of age) and hence perform better than those in the bottom (badly motivated or low skilled) for whom age plays a negative role in their performance. This result can be seen in Figures 3 and 4, where we plotted the conditional distribution of performances for individuals who, at the moment of the census were 21 and 30 years old. Consequently, in spite of having similar locations, the conditional distribution of performances of older students is more disperse than that of younger ones. As mentioned in the Introduction, the insignificance of the age variable in the OLS mean model might lead careless observers to the wrong conclusion that age has no effect in performance, ignoring that it has a non-trivial effect on the dispersion, a fact that has important consequences since more heterogeneous groups may require a different pedagogical treatment than younger and more homogeneous ones.

Next we explore the effect of working while studying. Variables *work-related* and *work-not-related* are dummy variables indicating with one, respectively, if the student has a job related to her subject of study, and whether she works in an unrelated job, being 'not working' the implicit omitted category. OLS results suggest a negative effect on performances: overall, jobs affect performances negatively, with a stronger effect in the case of those working in jobs not related to their careers. Quantile regression provides a more accurate characterization. Consider first the case of accountants. Once again, both effects are stronger in the bottom of the conditional distribution of performances. Interestingly, the effect of working in non-related jobs is consistently negative and significant, but the effect of

working in related jobs does not have a significant effect above the median. These are very relevant results since they imply that career specific jobs do not compromise performance for Accountancy students with relatively good performance[16]. The case of Law students is different. The dummy variable denoting jobs related to the career is never significant at all quantiles and in the OLS model. The effect of working in non-related jobs is similar to the one for accountants. This is a relevant result since it reveals that the dynamics of a career in Law is compatible with a job related to the practice of the Law without affecting performance, but also with the fact that students who do not work do not have a better performance than those who have jobs related to the career. The detrimental effect appears only in the case of those working in jobs not related to the career.

A much debated topic in the local literature is the relevance of the type of secondary education, where students who have the 'commercial' orientation are expected to have a relative advantage in Accountancy. Surprisingly the type of secondary school orientation has a homogeneous not significant effect on performances in both Accountancy and Law.

Marital status is homogeneously non-significant across most quantiles, and a similar result holds for Law students. Location variables have rather homogeneous effects, so quantile regression results do not add much to those revealed by OLS. Having to commute to attend college is not a relevant factor across all quantiles of the conditional distribution of performances. The fact that students reallocate to attend college has a homogeneously relevant and positive effect in performances, much in accordance with the idea that those willing to pay the fixed costs of reallocation are the relatively good students.

V. Conclusions

The main goal of this paper is to measure the effect of observable individual characteristics on the whole conditional distribution of performances. One of the main reasons for choosing this strategy is that in the case of educational policies it is necessary to complement the standard educational production function approach, by studying not only the mean

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[16] The Internship Law (Ley de Pasantías - National Law 25165-99) is quite explicit regarding the complementary nature of internships, defining them as 'supervised practices related to specialization and training' (art. 2) in order to obtain 'practical experience to complement theoretical training'.

effects of observable variables but also their impact on the shape of the distribution of performances. This is relevant since educational policies are often expected to promote equality of opportunities and possibilities, and hence distributive outcomes matter. Also, if policy actions are oriented towards the less advantaged, or any other specific group, it is important to assess whether the impact of a policy measure is homogeneous for all students, or whether average effects are actually an imprecise summary of a more complex reality that may benefit certain individuals systematically more than others.

Heterogeneities arise from interactions between unobserved and observed factors in the production of educational outcomes. Quantile regression methods are shown to provide a flexible framework to model these interactions between observed and unobserved factors, which are the source of non homogeneous effects on performance that alter its conditional distribution in subtle ways improperly summarized by mean OLS based methods.

This methodological framework is adopted and applied to the case of college students in Argentina, whose social and institutional characteristics, that combine free access, a flexible schedule and a diverse socio-economic composition of its students, provide ample sampling variability making it a relevant case study.

The empirical results of our research strongly suggest the presence of heterogeneous effects, which leaves ample room to question whether relevant factors like parental education or secondary school type are stronger or weaker for certain individuals. The results of this paper indicate that, overall, effects are found to be less relevant in the top of the distribution, in the sense that all factors that contribute positively to performance (better family background, not having to work, etc.) are stronger in the bottom. Hence, policies that enhance the possibilities of students initially in the lower part of the distribution have the dual effect of increasing their absolute performances (through their positive effect) and reduce disparities due to their stronger effect in this group of students. These results are important for the design of educational policies aimed at promoting equality of opportunities, since along the lines advanced by Roemer (1998), they must be tailored to compensate with external resources the different circumstances faced by students exerting similar levels of effort.

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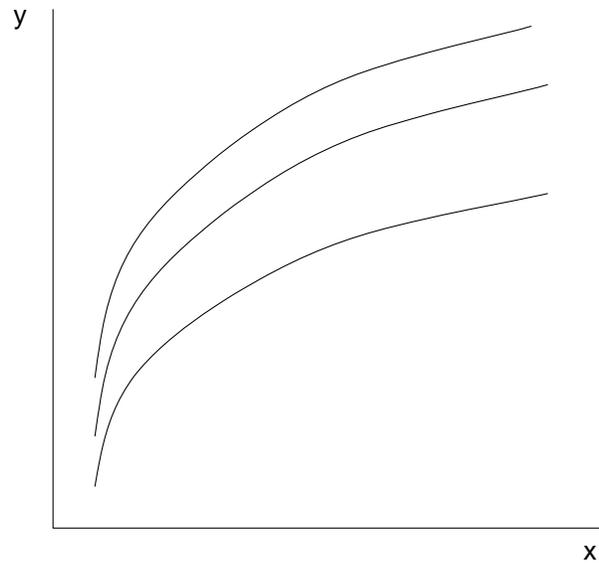
Appendix: Estimating Conditional Densities

In order to estimate the density of performances (*y*) conditional on a vector *x* of explanatory variables, we first obtain a random sample from the conditional distribution *y|x*. Machado and Mata (2005) suggest the following procedure to obtain random numbers based on an estimated model for the conditional quantiles. Assume that τ is a random variable uniformly distributed in (0,1). By the probability integral transformation theorem, if $y|x \sim F(Y|x)$

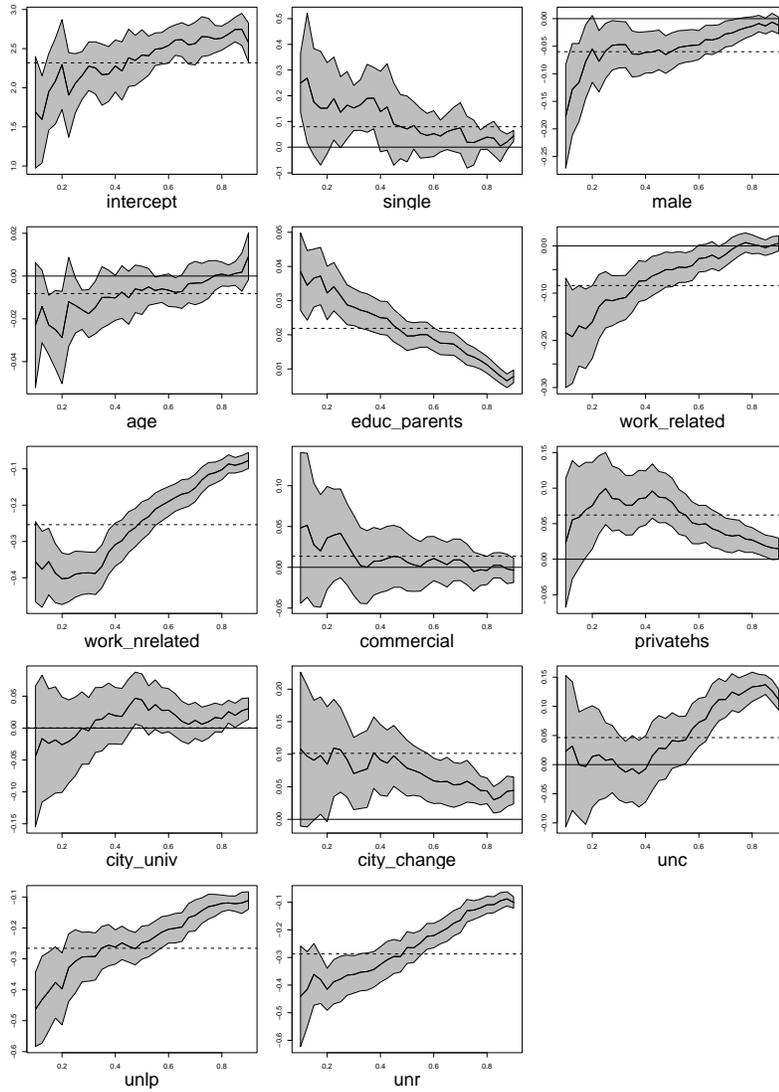$$Q_\tau(y|x) = F_{y|x}^{-1}(\tau) = x'\beta(\tau) \sim F_{y|x}.$$

Then, we can obtain a random sample of size *J* of *y|x* by first generating uniformly distributed random numbers τ_j, *j=1,…, J*, and then computing $x'\hat{\beta}(\tau_j)$,*j=1,…,J*, where $\hat{\beta}(\tau_j)$ are the estimates of the coefficients of the linear quantile regression for quantiles τ_j, *j=1,…, J*. In our case, the vector *x* is set at convenient values. For example, in the comparison between students with public vs. private secondary education, two samples were obtained by setting *x* at their sample averages, and then switching the dummy variable for secondary school background from zero to one.

Once there is available a random sample of *y|x*, an estimate of the conditional density is obtained by applying standard kernel methods on this random sample. The equivariance property of quantiles makes it straightforward to extend this mechanism to obtain random samples of any monotone transformation of *y*. In our case, since the model is estimated for the logs of performance, it is easy to see that $\exp(x'\beta(\tau_j))$, $j = 1,…,J$ is a random sample of the original variable in levels, when the model is estimated in natural logarithms.
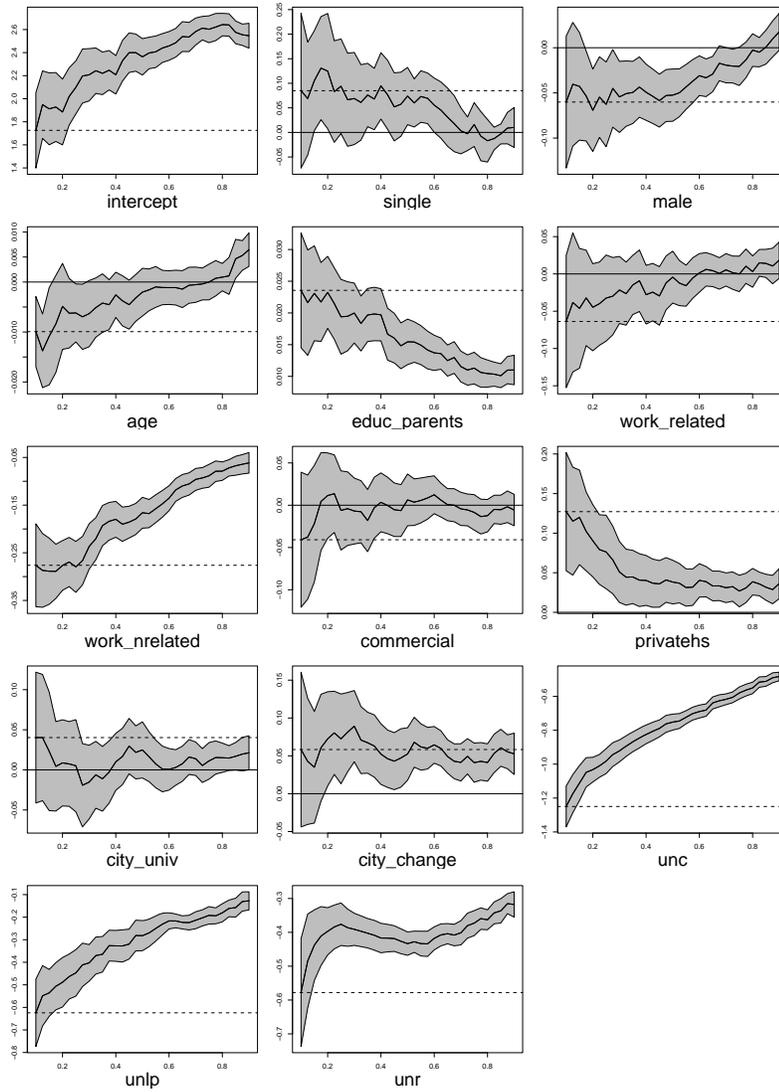
Figure 1
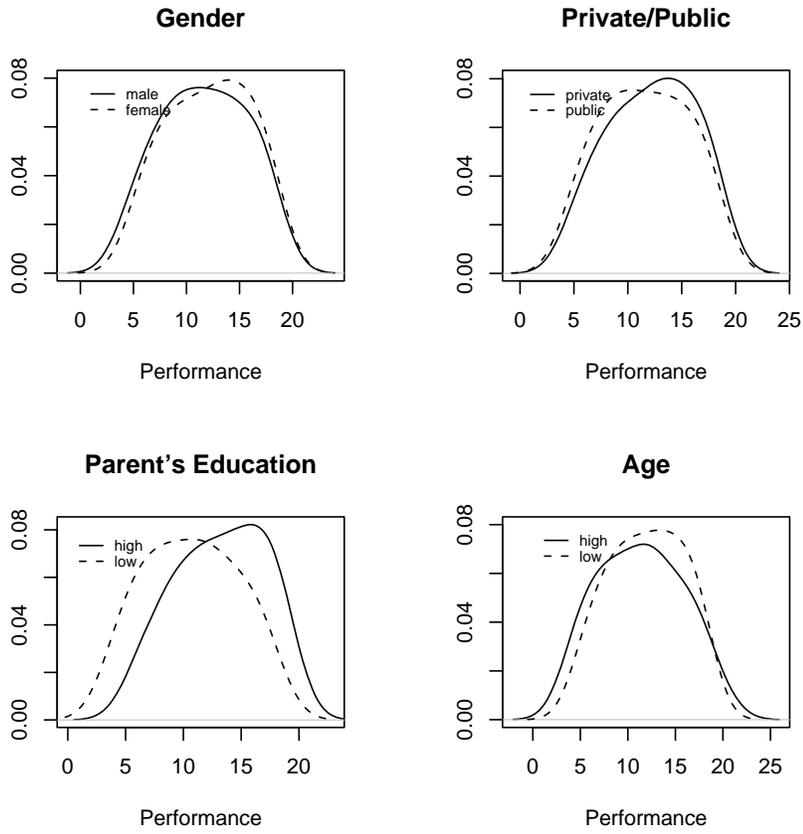**Production Functions for Different Conditional Quantiles**

Figure 2a)
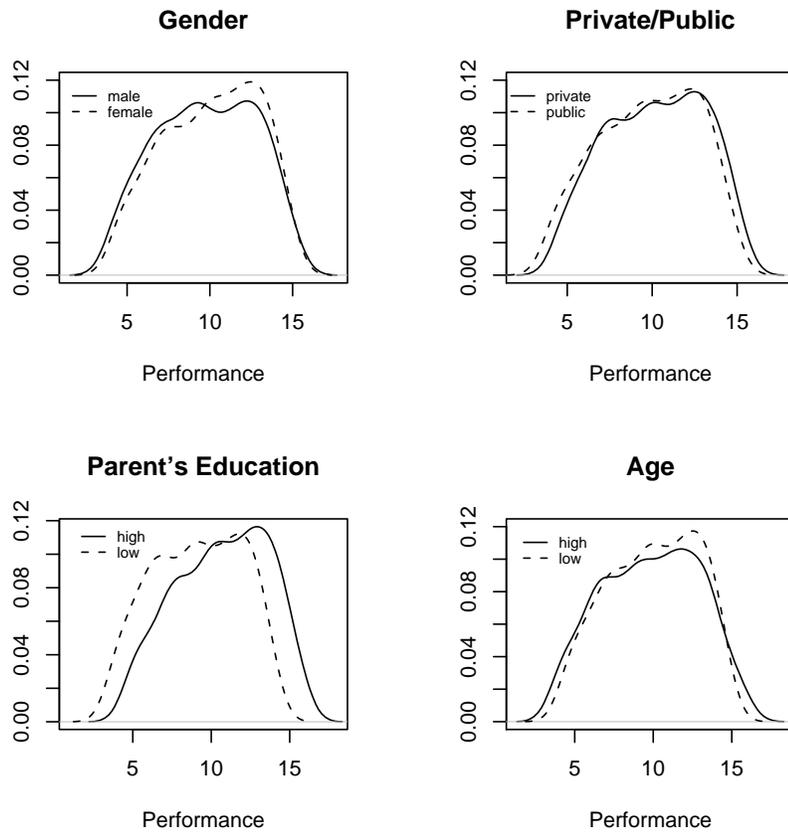**Quantile Regression Results: Accountancy**

Figure 2b)
Quantile Regression Results: Law

Figure 3
Conditional Densities. Accountancy

Figure 4
Conditional Densities. Law

Gender

Private/Public

Parent's Education

Age

Table 1
Variable Description and Summary Statistics.
Accountancy and Law sample - Cohort 1991

Name	Description	Accounting			Law		
		Mean	Percentile		Mean	Percentile	
			5%	95%		5%	95%
Performance Indicators							
performance	Number of courses passed	12.13	3	21	10.37	2	18
Explanatory Variables							
male	1 if male; 0 otherwise	0.50	0	1	0.41	0	1
age	Age in years	21.98	21	25	23.17	21	33
private	1 if private secondary school	0.49	0	1	0.44	0	1
commercial	1 if commercial secondary school	0.65	0	1	0.33	0	1
workrelated	1 if job related to program	0.41	0	1	0.22	0	1
worknotrelated	1 if job not related to program	0.26	0	1	0.40	0	1
workno	1 if student does not work	0.33	0	1	0.37	0	1
single	1 if single	0.95	1	1	0.89	0	1
cityuniv	1 if live in school area	0.75	0	1	0.74	0	1
citychange	1 if changed location	0.20	0	1	0.27	0	1
educparents	Parental education[†]	12.54	7	18	13.11	7	18
educfather	Father education	11.32	3.5	18	12.04	3.5	18
educmother	Mother education	11.05	3.5	18	11.68	3.5	18
Dummies for Universities							
uba	1 if UBA	0.49	0	1	0.56	0	1
unc	1 if UNC	0.19	0	1	0.22	0	1
unlp	1 if UNLP	0.14	0	1	0.09	0	1
unr	1 if UNR	0.17	0	1	0.12	0	1
Number of observations		3816			4812		

Source: CEUN 1994

[†] Maximum between father and mother education. Mother or father education when only one of them is present.

Table 2a)

Quantile Regression Results. Accountancy

Variable	Quantile					OLS	(a) THn. Null Hypothesis :	
	0,10	0,25	0,50	0,75	0,90		Location	Location/Scale
(Intercept)	1,687	2,057	2,418	2,649	2,578	2,318	1,406	1,546
	3,888	8,945	12,288	18,330	16,995	17,141		
single	0,250	0,136	0,071	0,018	0,044	0,079	2,026	1,008
	3,552	1,609	0,910	0,336	3,433	1,526		
male	-0,177	-0,058	-0,059	-0,021	-0,012	-0,060	1,150	1,887
	-3,101	-1,922	-2,916	-1,610	-1,354	-3,001		
age	-0,023	-0,014	-0,007	-0,002	0,009	-0,008	1,776	2,442
	-1,293	-1,750	-0,978	-0,306	1,393	-1,891		
educparents	0,038	0,031	0,020	0,013	0,008	0,022	2,321	2,670
	5,559	8,092	7,579	7,885	6,948	8,824		
workrelated	-0,184	-0,114	-0,050	0,001	0,006	-0,084	1,335	2,943
	-2,608	-3,144	-2,294	0,105	0,584	-3,488		
worknotrelated	-0,356	-0,390	-0,243	-0,115	-0,077	-0,254	3,439	3,518
	-5,298	-10,108	-7,652	-5,801	-5,806	-9,562		
commercial	0,048	0,042	0,006	-0,005	-0,004	0,014	1,488	1,022
	0,860	1,262	0,293	-0,361	-0,404	0,641		
private	0,023	0,099	0,080	0,034	0,015	0,062	2,028	1,750
	0,417	3,231	3,850	2,629	1,656	3,065		
cityuniv	-0,045	-0,013	0,044	0,010	0,031	0,000	1,289	1,346
	-0,664	-0,349	1,769	0,637	2,979	0,015		
citychange	0,108	0,107	0,079	0,052	0,044	0,101	0,939	1,109
	1,499	2,702	3,014	3,202	3,538	3,766		
n.unc	0,023	0,007	0,041	0,119	0,111	0,046	2,047	1,733
	0,292	0,188	1,423	6,577	10,352	1,611		
n.unlp	-0,464	-0,308	-0,247	-0,131	-0,111	-0,266	1,821	3,174
	-6,357	-4,949	-7,619	-5,371	-6,509	-8,499		
n.unr	-0,440	-0,378	-0,264	-0,128	-0,101	-0,287	2,890	3,076
	-3,983	-7,527	-7,543	-6,175	-7,982	-9,809		
Adj -R Sq						0,102		
(b) Tn							39,331	20,920
Obs	3.816							

Note: t-values are given in the second line below each parameter estimate.
(a) THn: Test statistics testing whether each individual slope parameters satisfy the null hypothesis.
(b) Tn: Joint test statistic of the hypothesis that all the slope parameters of the model satisfy the hypothesis.

Table 2b)
Quantile Regression Results. Law

Variable	Quantile 0,10	0,25	0,50	0,75	0,90	OLS	(a) THn. Null Hypothesis : Location	Location/Scale
(Intercept)	1,726	2,098	2,363	2,603	2,546	2,181	0,865	0,962
	8,675	15,000	24,638	36,780	38,895	27,077		
single	0,085	0,094	0,074	0,016	0,010	0,068	2,069	1,136
	0,887	1,605	2,090	0,589	0,408	2,107		
male	-0,060	-0,063	-0,052	-0,021	0,018	-0,027	1,732	2,479
	-1,353	-2,198	-2,982	-1,607	1,421	-1,605		
age	-0,010	-0,006	-0,002	0,000	0,006	-0,001	2,328	3,259
	-2,324	-1,753	-0,698	0,000	3,178	-0,294		
educparents	0,024	0,019	0,015	0,011	0,011	0,019	2,121	0,764
	4,283	5,415	7,079	7,441	7,792	9,084		
nworkrelated	-0,064	-0,032	-0,004	0,000	0,018	-0,019	0,822	0,839
	-1,181	-0,922	-0,201	0,000	1,247	-0,807		
nworknotrelated	-0,276	-0,280	-0,166	-0,089	-0,061	-0,186	1,915	2,458
	-5,229	-8,608	-8,424	-6,073	-4,672	-9,477		
commercial	-0,041	-0,006	0,006	-0,008	-0,006	-0,001	1,485	1,381
	-0,841	-0,217	0,338	-0,664	-0,506	-0,051		
private	0,127	0,076	0,038	0,027	0,036	0,058	0,882	1,953
	2,802	2,701	2,279	2,215	3,143	3,349		
cityuniv	0,040	0,005	0,025	0,011	0,021	0,004	0,800	0,927
	0,812	0,148	1,168	0,805	1,648	0,184		
citychange	0,058	0,072	0,052	0,041	0,053	0,067	1,060	0,914
	0,939	2,010	2,489	2,608	3,171	3,188		
n.unc	-1,250	-0,982	-0,752	-0,580	-0,482	-0,799	2,032	2,757
	-17,051	-21,916	-26,206	-26,937	-31,484	-35,656		
n.unlp	-0,624	-0,447	-0,282	-0,192	-0,128	-0,333	2,038	2,093
	-6,876	-7,122	-6,956	-8,154	-5,223	-11,002		
n.unr	-0,578	-0,376	-0,433	-0,373	-0,318	-0,418	0,871	1,564
	-5,963	-9,839	-20,664	-16,592	-13,945	-15,382		
Adj -R Sq						0,261		
(b) Tn							17,225	15,790
Obs	4812							

Note: t-values are given in the second line below each parameter estimate.
(a) THn: Test statistics testing whether each individual slope parameters satisfy the null hypothesis.
(b) Tn: Joint test statistic of the hypothesis that all the slope parameters of the model satisfy the hypothesis.