Económica, La Plata, Vol. LI, Nro. 1-2, 2005

CHANGES IN THE PANAMANIAN WAGE STRUCTURE: A QUANTILE REGRESSION ANALYSIS[1,2]

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1. Introduction

The evolution of the wage structure is an important area of research in labor economics. Technological innovations, changes in the distribution of education and in the structure of the labor and product markets are likely to alter the demand for and supply of different skill attributes.

In developed countries, the change in the wage structure has recently received considerable attention. During the 1980s, the wage structure in the United States changed dramatically. In particular, one observes sharp changes in wage inequality and dramatic increases in wage differentials by education and by experience (see, among others, Bound and Johnson (1992) and Katz and Murphy (1992)). Wage dispersion reached its highest levels since the 1940s (see Goldin and Margo (1992)), growing considerably within socio demographic groups (see Buchinsky (1994) and Juhn et al. (1993)). In the UK, wage dispersion has also risen sharply since the late 1970s (see Schmitt (1995)). One common explanation for these phenomena is that the demand for labor has shifted from "less-skilled" to "highly-skilled" workers. Technical changes have been posited as the main reason for these demand shift (see, among others, Davis and Haltiwanger (1991), Bound and Johnson (1992) and Katz and Murphy (1992)). Another explanation stresses the role of foreign competition, which led to a decline in the manufacturing sector and in turn to greater demand for more

[1] JEL Classification: J30 and J31.
Keywords: Wage differentials, wage inequality and quantile regression.
[2] We give thanks to M. Gonzalez-Rozada, L. Gasparini, J.L. Moreno, O. Zambrano and participants at the NIP conference at UTDT.
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"highly-educated" workers (see Murphy and Welch (1991)). However, wage inequality increased substantially less, if at all, in the rest of the developed countries during this same period (see Nickell and Layard (2000)).

The empirical evidence about the evolution of wages in developing countries is scant. In this paper we contribute to fill this gap by studying the evolution of the wage structure in Panama for the period 1982-1997. We provide a simple characterization of the way in which the distribution of male wages has evolved in Panama during the last two decades. We model the (conditional) distribution of wages by means of the quantile regression technique and apply this model to study the male wage distribution and its evolution during the last two decades in Panama. The advantage of adopting this modeling strategy is that it allows us to identify wage changes not only between but also within socio demographical groups during the period under study.

The technique of *quantile regression* introduced by Koenker and Bassett (1978) has recently received a lot of attention. The quantile regression model extends the notion of ordinary quantiles in a location model to a more general class of linear models in which the conditional quantiles have a linear form. Thus, the quantile regression approach is a parametric way to explore the conditional distribution of a scalar random variable. In this paper, we explore different parts of the conditional distribution of wages by studying a set of quantile regressions, which provides us with a rich characterization of the conditional distribution of wages. In addition, and more importantly, the quantile regression technique also allows us to investigate whether wage inequality within groups, measured as the dispersion of wages within demographic or skill groups, has increased during the last two decades.

The rest of the paper is organized as follows: Section 2 describes intuitively the quantile regression model. It also motivates the approach adopted in this paper. Section 3 presents the empirical results. Section 4 summarizes the conclusions of the paper.

2. The quantile regression approach

The purpose of the classical least squares estimation is to answer the following question: how does the conditional expectation of a random variable Y, E(Y|X), respond to some explanatory variables X? The quantile regression model of Koenker and Bassett (1978) poses this question for any quantile of the conditional distribution of Y. In other words, it investigates the influence of X on the shape of the entire distribution of Y.

Given a random sample (of wages) $w_1, \ldots, w_n$, its θth sample quantile can be found as

$$\underset{\mu \in \Re}{\operatorname{argmin}} \sum_{i=1}^{N} \rho_\theta (w_i - \mu)$$

where

$$\rho_\theta(u) = u\,[\theta - I(u < 0)]$$

and where $u = w - \mu$, $\theta \in (0,1)$ and I(.) represents the indicator function. Having succeeded in defining the unconditional quantiles as an optimization problem, we now define conditional quantiles in an analogous fashion. Thus, to obtain conditional quantile (linear) functions we solve:

$$\underset{\beta_\theta \in \Re^k}{\operatorname{argmin}} \sum_{i=1}^{N} \rho_\theta (w_i - x_i' \beta_\theta)$$

Accordingly, the quantile regression model of Koenker and Bassett (1978) can be written as

$$w_i = x_i' \beta_\theta + u_{\theta i} \text{ with } Q_\theta(w_i \mid x_i) = x_i' \beta_\theta \text{ (i = 1, …, N)}$$

where β_θ and x_i are vectors of dimension (k × 1), and $x_{1i} \equiv 1$. $Q_\theta(w| x)$ denotes the θth conditional quantile of w given x. Lastly, let $f_u(. \mid x)$ denote the density of u_θ given x.

Under certain regularity conditions (see Koenker and Bassett (1978)), it can be shown that:

$$\sqrt{n}\left(\hat{\beta}_\theta - \beta_\theta\right) \to N(0, \Lambda_\theta)$$

where

$$\Lambda_\theta = \theta(1-\theta)\ [E(f_{u\theta}(0 \mid x_i)\ x_i x_i^{'})]^{-1}\ E[x_i x_i^{'}]\ [E(f_{u\theta}(0 \mid x_i)\ x_i x_i^{'})]^{-1}$$

The main problem in estimating Λ_θ arises with regard to $f_{u\theta}(0|x)$. Koenker and Bassett (1982) discuss the estimation of Λ_θ, and in particular how to estimate the density function of the errors evaluated at each of the required quantiles. Estimation of this density is not straightforward, but more serious, Rogers (1993) reports that in the presence of heteroscedasticity, the asymptotic estimator of Λ_θ underestimates the standard errors. Thus, if heteroscedasticity is suspected, which is often a reason to rely on the quantile regression model, it is necessary to rest on an alternative method for estimating the standard errors. Thus, to overcome this nuisance, design matrix bootstrap standard errors are normally computed (see Buchinsky, 1994).

The quantile regression was originally proposed as a robust alternative to the ordinary least squares estimator for estimating the parameters of a linear regression function. In this context, robust connotes a certain flexibility of the statistical procedures to deviations from the distributional assumptions of the hypothesized models. Nevertheless, in our study, and in the related literature (see, among others, Buchinsky (1994) and Gosling et al. (2000)), the interest resides in estimating the parameters of the conditional distribution of wages at different quantiles rather than in seeking a robust alternative to ordinary least squares. Therefore, it is necessary to substantiate the sense in which it is interesting to study, for example, the educational wage premium at different quantiles of the conditional distribution of wages.

First, for any schooling group, its conditional distribution of wages presumably reflects unobserved abilities. Gosling et al. (2000) emphasize that the distribution of wages can be split into two components: a component that may be attributed to the distribution and returns to observed skills and a component that may be attributed to the unobserved characteristics of the workers and their jobs. What is more, these two components interact with each other. Thus, there is no reason to require that the wage differentials among schooling groups should be the same at every quantile of the (conditional) distribution of wages. Precisely, the quantile regressions are a (parametric) way to explore these differences. Consequently, by modeling the conditional distribution of wages applying the quantile regression model, we allow the unobserved component of wages to interact with the available measures of observed skills.

Second, as we mentioned in the introduction, during the 1980s, some developed countries shared a pattern of rising wage inequality. The changes occurred not only in the rewards to the observable skills but also within narrowly defined groups. Since the quantile regression technique allows us to trace the conditional distribution of any random variable, it provides us with an extremely useful tool for examining changes in the shape of the conditional distribution of wages.

A simple way to study the changes in wage inequality is to study the changes in the interdecile range of the wage distribution or the changes in any other range of the wage distribution such as, for example, the interquartile range. Alternatively, since the quantile regression technique allows us to trace the entire conditional wage distribution, it provides an extremely useful tool for examining changes in the shape of that conditional distribution. Buchinsky (1994), for example, considers two measures of within-group inequality defined as the difference between specific conditional quantiles. Consequently, Buchinsky's measures depend on the model's covariates and therefore they convey more information than the one provided by the change in any range of the wage distribution. In this study we focus on the difference between the 0.9 and 0.1 conditional quantiles.

We now illustrate our discussion by means of an extremely simple example constructed in the sample space.[4] Suppose that there are only three different levels of skills in the economy. We denote them unskilled (U), semi-skilled (SS) and skilled (S). Thus, in this example, the conditional quantiles of wages given the skill level of the individual is given by

[4] The example is not realistic in that it is oversimplified. In practice, we never obtain the quantile regression coefficients in the simple way they are obtained in this example.

$$Q_{\theta}(w \mid x) = x^{'}\beta_{\theta} = \alpha_{\theta} + \alpha_{\theta}(ss)\ dss + \alpha_{\theta}(s)\ ds \qquad (1)$$

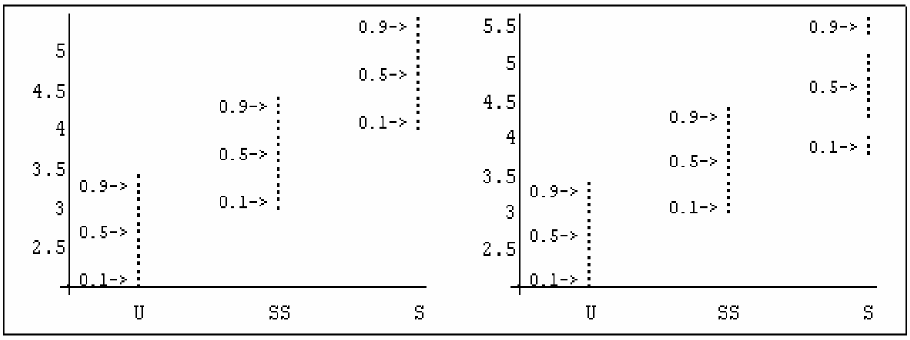
where dss and ds are the respective dummy variables that indicate the skill level of the individual observations.

Figure 1 shows a hypothetical sample of log wages (w). Panel A illustrates the case in which the conditional distribution of w given x is symmetric and homoscedastic. The symmetry of the conditional distribution implies that the conditional mean coincides with the conditional median while the homoscedasticity of the distribution implies that the estimated coefficients but the intercept are the same at every quantile of the conditional distribution of wages.

It is useful to conceive the conditional distribution of w as a set of cells containing the observations of w for any skill group. We denote these cells U, SS and S. Then, by marking any desired sample quantile in cell U, we obtain the intercept of the respective θ-quantile regression. Doing the same in cells S and SS, we respectively obtain the desired sample quantiles $Q_{\theta}(w \mid SS)$ and $Q_{\theta}(w \mid S)$. Finally, and only in this extremely simplified example, we obtain the desired coefficients in an straightforward way starting from equation (1):

$$\alpha_{\theta}(ss) = Q_{\theta}(w \mid SS) - \alpha_{\theta} \quad \text{and} \quad \alpha_{\theta}(s) = Q_{\theta}(w \mid S) - \alpha_{\theta} \qquad (2)$$

Figure 1



Panel A **Panel B**

In Figure 1 we have marked the 0.1-sample quantile, the median and the 0.9-sample quantile. The only difference between panels A and B is in cell S. In panel B, we move up and down some observations in such a way that the conditional distribution of w given x remains symmetric. Nonetheless, it has become heteroscedastic. Since there are no differences in cells U and SS between panels A and B, we obtain the same estimates for both α_θ and $\alpha_\theta(\text{ss})$ at every θ*th* quantile whether we use the hypothetical data set in panel A or the data set drew in panel B. However, the estimated coefficient $\alpha_\theta(\text{s})$ from the data set in panel A may differ from that estimated from the data set drawn in panel B. For this latter hypothetical data set, the coefficient of the skilled dummy variable is not the same at every quantile of the conditional distribution. It is in that sense that the quantile regressions allow us to describe (parametrically) the conditional wage distribution. In our example, $\alpha^{\text{B}}_{0.1}(\text{s}) < \alpha^{\text{A}}_{0.1}(\text{s})$ and $\alpha^{\text{B}}_{0.9}(\text{s}) > \alpha^{\text{A}}_{0.9}(\text{s})$. Note that Buchinsky's (1994) within-group measure of wage dispersion, i.e. $\alpha_{0.9}(\text{s}) - \alpha_{0.1}(\text{s})$, is larger for the data set in panel B than for the data set in panel A, capturing the higher dispersion in cell S. Note further that the interdecile range of the wage distribution is also larger for the data set in panel B than for the data set in panel A. However, this unconditional statistic conveys less information than the one proposed in Buchinsky (1994).

Note also that both estimated regression functions are identical. Of course, the example has been built with this intention. Notwithstanding, it reveals the way in which the quantile regression model may be applied to study an interesting issue such as wage inequality. A drawback of the example is that it may suggest that quantile regressions ignore sample information because any of them pass only through three sample points. This is not so, since the entire sample is used to determine the estimated coefficients.

3. Empirical results

In this section we study the Panamanian wage structure and its evolution by modeling some conditional quantiles of this distribution for the period 1982-1997. The analysis uses a reduced form equation and emphasizes the returns to education and its pattern of change over time. Nevertheless, it is worth noting that the reported effect of any variable on wages only refers to the effect of that variable on a particular quantile of the conditional distribution of wages. This means that the coefficients we obtain cannot be interpreted as estimators of the causal effect of independent variables on wages. Particularly, these estimated coefficients cannot be taken as the estimators of internal rates of return to education.

We estimate the parameters of a standard earnings equation at the 0.1, 0.5, and 0.9 quantiles. We also report standard ordinary least squares estimates for comparison. The data is gathered from the ongoing Panamanian household survey, which frame covers all but the indigenous population of the country. The dependent variable is the logarithm of the hourly earnings of the sampled individuals in their main occupations. The models we estimate include the following variables: set of dummy variables indicating the educational level of the individual, set of dummy variables indicating the region (province) of residence of each worker in the sample and an additional dummy variable indicating whether the individual works in the canal zone and the number of years of potential experience (PE).

Available information about educational level attained by an individual is grouped in four groups: at most complete primary school, incomplete secondary school, complete secondary school, and complete tertiary degree. The schooling dummy variables measure the maximum educational level reached by an individual and if it has been completed. The base category is the group with at most complete primary school and individuals with incomplete tertiary degree are excluded from the analysis. Potential experience is measured as follows: PE = Age_i - 15 (where *Age* is the age of the individual) if the schooling achievement of individual *i* is at least primary school; PE = Age_i - 16 if the maximum schooling achievement of individual *i* is incomplete secondary school; PE = Age_i - 18 if the maximum schooling achievement of individual i is complete secondary school; and PE = Age_i - 25 if individual i has obtained a tertiary degree.[5]

We concentrate exclusively on describing the changes in the male wage structure during the sample period. Therefore, we include only male wage earners between sixteen and fifty-five years old and exclude from the sample self-employed, owner-managers and unpaid workers, as well as employed students. The selection of the upper age boundary is based on the retirement age prevalent during most of the sample period.

Finally, we divide the sample into three groups of potential experience (1 to 5, 6 to 19 and 20 to 29 years of PE) and estimate the earnings functions at the different conditional quantiles for each of these three groups. The covariance matrix of the vector of estimated coefficients is obtained by means of bootstrapping techniques for the reasons explained in the previous section.

The results are presented in tables I to IV in the appendix. The following are the most important results. As is the case in every country, *ceteris paribus,* more educated workers earn more than less educated workers. In Panama, this is true for each of the conditional quantiles studied. What is more, the wage differentials by schooling group are similar for the three groups of potential experience into which we divided the population.

Wage differentials between schooling groups have not changed in any regular manner over the sample period. In particular, we do not observe any trend in wage differentials between schooling groups during the sample period. In effect, and contrary to the evidence from some developed

[5] The measure of PE adopted is in the spirit of the measure of potential experience (PE*) implemented by some authors, where PE* = Min(age-years of schooling-x, age-y), where x and y are typically in the intervals [5,7] and [17,18] respectively (see, e.g., Katz and Murphy (1992) and Buchinsky (1994)). PE* restricts the potential experience of any individual to be below age-y and therefore, it assumes that an individual acquires his relevant general experience since he is y years old. It seems reasonable in this case to choose y equal to sixteen given the high proportion of workers who have an educational achievement below complete secondary school and that the proportion of workers aged less than sixteen years old is negligible during the sample period. To ensure that no individual has a negative PE, a few observations were eliminated from the sample.

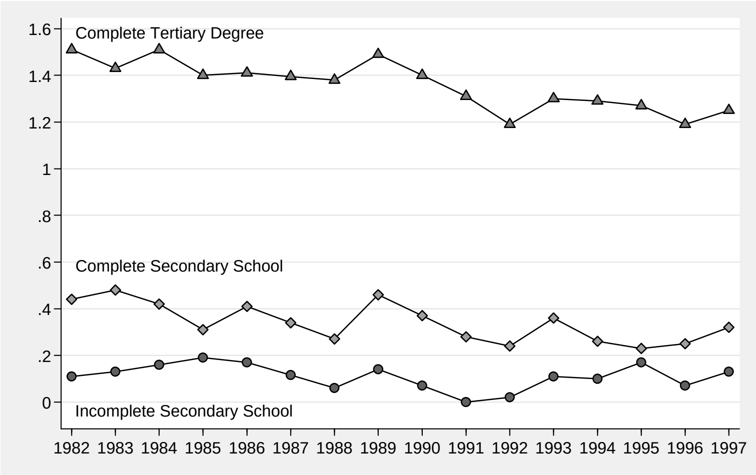
countries such as the United States (see Buchinsky (1994)), we do not observe any trend suggesting a significant increase in the wage premium of the most qualified workers. This is true for each of the three groups of potential experience studied. Figure 2 shows this result for the 0.5 conditional quantile. We may also add that this conclusion is valid for the whole (conditional) wage distribution since it is valid for all the (conditional) quantiles we study in the paper, and not only for the mean or the median conditional quantiles.

In Table IV (in the appendix) we present the results of testing the equality of coefficients associated to schooling-level dummy variables at the different quantiles. The table shows the statistic of contrast and the associated p-value. For almost every test we do not reject the null hypothesis. This result allows us to conclude that the educational wage premia are similar at different quantiles of the conditional distribution of wages and also for the three groups of potential experience into which we divided the population. This result needs to be emphasized because it represents a distinct feature of Panamanian wage structure: a fairly symmetric wage distribution, which is a highly infrequent feature.

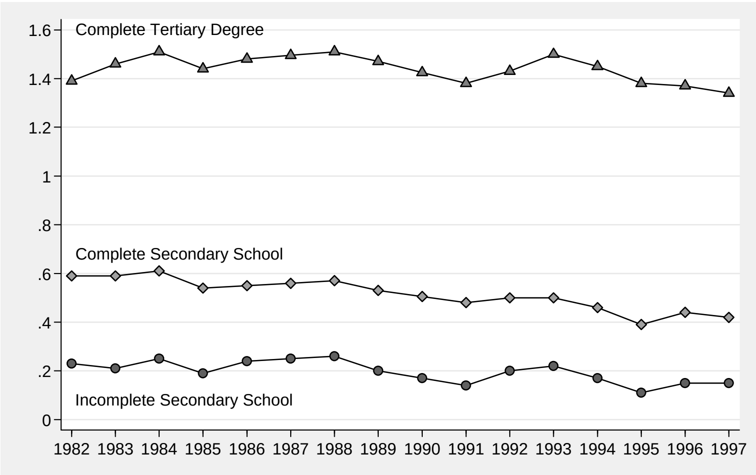
Additionally, Figure 3 displays no trend in our measure of within-group wage inequality for any of the groups considered. This result also contrasts with the evidence from some developed countries such as the United States and UK during the last two decades (see Buchinsky (1994) and Gosling et al. (2000)). Thus, to conclude, it is possible to assert that in general, Panama shows a pretty stable wage structure over the period studied.

Figure 2. **Median Regression**

Panel A. **Wage differential by schooling group: 1-to-5-years-of-experience group**



Panel B. **Wage differential by schooling group: 6-to-19-years-of-experience group**



Panel C. Wage differential by schooling group: 20-to-29-years-of-experience group

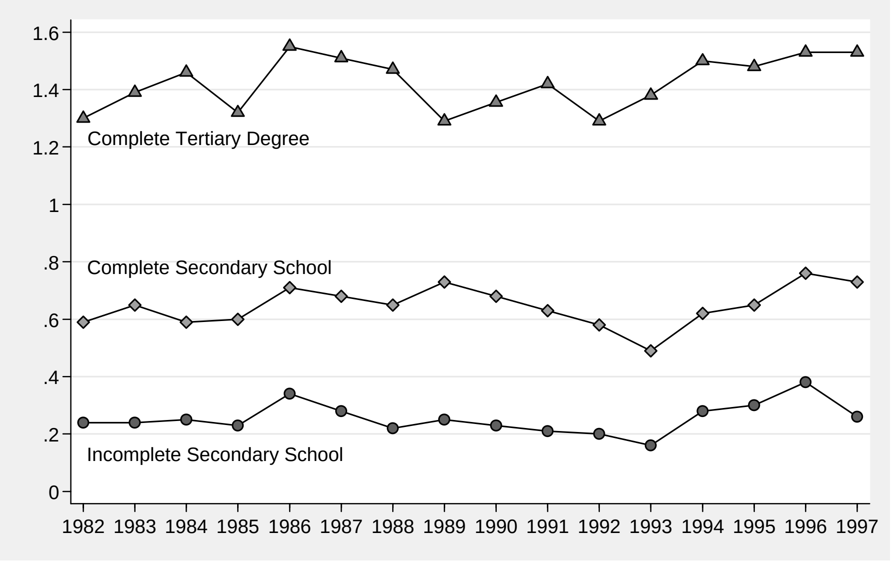
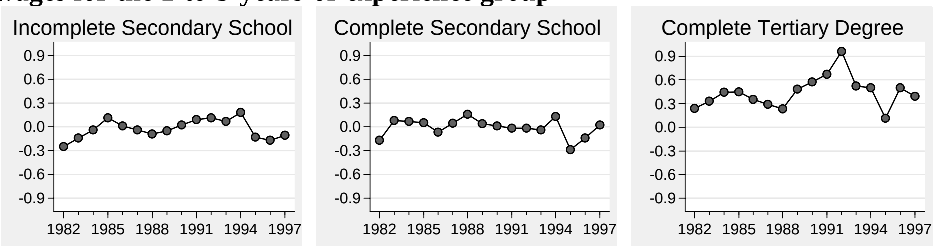
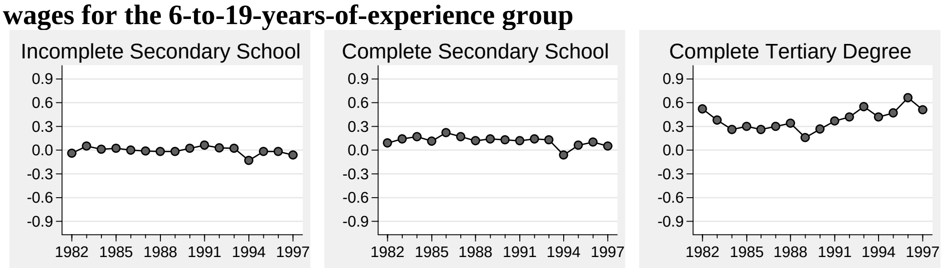


Figure 3. Within group wage dispersion

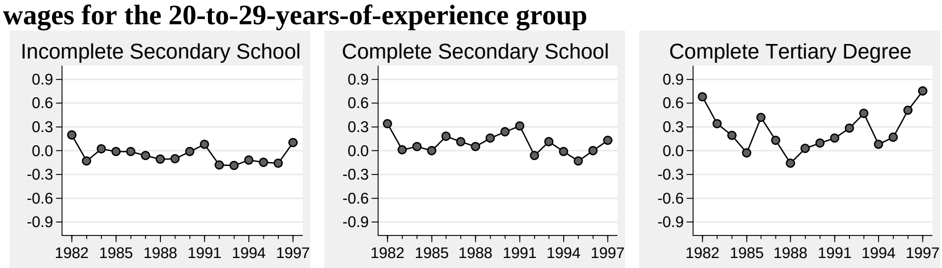
Panel A. Difference between 0.1 and 0.9 conditional quantiles of monthly wages for the 1-to-5-years-of-experience group



Panel B. Difference between 0.1 and 0.9 conditional quantiles of monthly wages for the 6-to-19-years-of-experience group



Panel C. Difference between 0.1 and 0.9 conditional quantiles of monthly wages for the 20-to-29-years-of-experience group



4. Conclusions

In this paper we present evidence on the evolution of the Panamanian wage structure for the period 1982-1997. We model the (conditional) wage distribution using the quantile regression technique and apply this model to study the changes in the male wage distribution during the sample period. The advantage of adopting this modeling strategy is that it allows us to identify wage changes not only between but also within demographic groups during the period under study.

The following are the conclusions of our study. As is the case in every country, ceteris paribus, more educated workers earn more than less educated workers. In Panama, this is true for each of the conditional quantiles studied.

In general, during the period considered, we do not observe any trends in the change in wage differentials between schooling groups. In particular, there is not any trend suggesting a significant increase in the wage premium of the most qualified workers. This conclusion is valid for the whole (conditional) wage distribution and not just for its central moments. Additionally, we do not find any trend in the conditional measure of within group inequality considered. Finally, it is worth noting that the pattern of change of wage premia has been the same for all the potential experience groups. Thus, as conclusion, we can say that Panama shows a fairly stable wage structure over the period studied.

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Table I. Conditional quantiles
Dependent variable: logarithm of monthly wage earnings (1-to-5-years-of-experience group)

Year	Incomplete secondary school	Complete secondary school	Complete tertiary degree	Incomplete secondary school	Complete secondary school	Complete tertiary degree	Incomplete secondary school	Complete secondary school	Complete tertiary degree	Incomplete secondary school	Complete secondary school	Complete tertiary degree
	Quantile: 0.1			Quantile: 0.5			Quantile: 0.9			Mean (OLS)		
1982	0.23 (0.119)	0.54 (0.122)	1.34 (0.127)	0.11 (0.072)	0.44 (0.077)	1.51 (0.098)	-0.02 (0.118)	0.37 (0.131)	1.58 (0.137)	0.08 (0.063)	0.45 (0.063)	1.44 (0.075)
1983	0.25 (0.190)	0.53 (0.158)	1.42 (0.199)	0.13 (0.062)	0.48 (0.058)	1.43 (0.073)	0.11 (0.082)	0.61 (0.093)	1.75 (0.120)	0.20 (0.068)	0.60 (0.066)	1.52 (0.077)
1984	0.22 (0.179)	0.56 (0.159)	1.38 (0.199)	0.16 (0.052)	0.42 (0.063)	1.51 (0.122)	0.18 (0.119)	0.63 (0.107)	1.82 (0.140)	0.26 (0.059)	0.53 (0.059)	1.55 (0.069)
1985	0.14 (0.094)	0.26 (0.104)	1.10 (0.128)	0.19 (0.096)	0.31 (0.095)	1.40 (0.114)	0.25 (0.118)	0.31 (0.115)	1.55 (0.155)	0.13 (0.060)	0.29 (0.064)	1.35 (0.071)
1986	0.25 (0.154)	0.57 (0.133)	1.36 (0.179)	0.17 (0.057)	0.41 (0.062)	1.41 (0.089)	0.26 (0.108)	0.50 (0.120)	1.71 (0.172)	0.23 (0.061)	0.47 (0.061)	1.45 (0.068)
1988	0.09 (0.190)	0.32 (0.187)	1.30 (0.201)	0.06 (0.076)	0.27 (0.071)	1.38 (0.107)	0.00 (0.157)	0.48 (0.186)	1.53 (0.169)	0.07 (0.087)	0.35 (0.084)	1.46 (0.090)
1989	0.28 (0.148)	0.51 (0.121)	1.16 (0.206)	0.14 (0.095)	0.46 (0.097)	1.49 (0.083)	0.23 (0.084)	0.55 (0.104)	1.64 (0.138)	0.21 (0.075)	0.54 (0.074)	1.53 (0.078)
1991	-0.15 (0.180)	0.38 (0.111)	0.90 (0.190)	0.00 (0.129)	0.28 (0.093)	1.31 (0.118)	-0.06 (0.178)	0.36 (0.202)	1.57 (0.263)	-0.12 (0.096)	0.31 (0.085)	1.26 (0.096)
1992	-0.12 (0.188)	0.32 (0.131)	0.83 (0.155)	0.02 (0.060)	0.24 (0.054)	1.19 (0.110)	-0.01 (0.119)	0.30 (0.102)	1.79 (0.242)	0.00 (0.082)	0.26 (0.073)	1.25 (0.079)

Year	Quantile: 0.1			Quantile: 0.5			Quantile: 0.9			Mean (OLS)		
	Incomplete secondary school	**Complete secondary school**	**Complete tertiary degree**	**Incomplete secondary school**	**Complete secondary school**	**Complete tertiary degree**	**Incomplete secondary school**	**Complete secondary school**	**Complete tertiary degree**	**Incomplete secondary school**	**Complete secondary school**	**Complete tertiary degree**
1993	0.07 (0.144)	0.47 (0.101)	1.04 (0.125)	0.11 (0.069)	0.36 (0.071)	1.30 (0.121)	0.14 (0.157)	0.43 (0.142)	1.56 (0.218)	0.08 (0.070)	0.38 (0.064)	1.29 (0.074)
1994	0.12 (0.121)	0.34 (0.108)	1.18 (0.160)	0.10 (0.067)	0.26 (0.053)	1.27 (0.097)	0.30 (0.135)	0.47 (0.110)	1.68 (0.163)	0.18 (0.069)	0.33 (0.063)	1.34 (0.072)
1995	0.39 (0.216)	0.60 (0.203)	1.43 (0.203)	0.17 (0.062)	0.23 (0.044)	1.27 (0.071)	0.26 (0.093)	0.31 (0.087)	1.54 (0.096)	0.29 (0.068)	0.36 (0.059)	1.35 (0.067)
1996	0.28 (0.111)	0.51 (0.092)	0.85 (0.136)	0.07 (0.061)	0.25 (0.056)	1.19 (0.101)	0.11 (0.128)	0.37 (0.096)	1.35 (0.132)	0.10 (0.087)	0.31 (0.078)	1.08 (0.089)
1997	0.33 (0.140)	0.51 (0.137)	1.12 (0.153)	0.13 (0.069)	0.32 (0.063)	1.25 (0.076)	0.22 (0.115)	0.53 (0.142)	1.51 (0.185)	0.25 (0.105)	0.48 (0.093)	1.32 (0.108)

Note: Standard errors are bootstrapped standard errors, computed with one hundred replications.

Table II. **Conditional quantiles**

Dependent variable: logarithm of monthly wage earnings (6-to-19-years-of-experience group)

Year	Quantile: 0.1			Quantile: 0.5			Quantile: 0.9			Mean (OLS)		
	Incomplete secondary school	Complete secondary school	Complete tertiary degree	Incomplete secondary school	Complete secondary school	Complete tertiary degree	Incomplete secondary school	Complete secondary school	Complete tertiary degree	Incomplete secondary school	Complete secondary school	Complete tertiary degree
1982	0.23 (0.045)	0.49 (0.044)	1.28 (0.065)	0.23 (0.029)	0.59 (0.032)	1.39 (0.052)	0.19 (0.065)	0.58 (0.076)	1.80 (0.118)	0.21 (0.030)	0.58 (0.033)	1.46 (0.045)
1983	0.22 (0.053)	0.47 (0.051)	1.33 (0.077)	0.21 (0.033)	0.59 (0.033)	1.46 (0.062)	0.27 (0.050)	0.61 (0.054)	1.71 (0.053)	0.28 (0.031)	0.62 (0.031)	1.52 (0.040)
1984	0.22 (0.038)	0.54 (0.042)	1.46 (0.060)	0.25 (0.029)	0.61 (0.035)	1.51 (0.059)	0.23 (0.048)	0.71 (0.063)	1.72 (0.077)	0.25 (0.028)	0.63 (0.031)	1.55 (0.038)
1985	0.18 (0.045)	0.46 (0.059)	1.38 (0.103)	0.19 (0.032)	0.54 (0.037)	1.44 (0.040)	0.20 (0.043)	0.57 (0.059)	1.68 (0.064)	0.19 (0.029)	0.53 (0.031)	1.48 (0.039)
1986	0.19 (0.062)	0.36 (0.066)	1.34 (0.086)	0.24 (0.037)	0.55 (0.036)	1.48 (0.066)	0.19 (0.057)	0.58 (0.050)	1.60 (0.095)	0.24 (0.030)	0.54 (0.033)	1.50 (0.040)
1988	0.22 (0.053)	0.50 (0.057)	1.32 (0.061)	0.26 (0.037)	0.57 (0.045)	1.51 (0.059)	0.20 (0.060)	0.62 (0.079)	1.66 (0.083)	0.25 (0.034)	0.57 (0.035)	1.51 (0.041)
1989	0.20 (0.055)	0.46 (0.061)	1.36 (0.079)	0.20 (0.044)	0.53 (0.039)	1.47 (0.043)	0.18 (0.066)	0.60 (0.061)	1.52 (0.057)	0.22 (0.037)	0.57 (0.037)	1.49 (0.043)
1991	0.10 (0.048)	0.38 (0.052)	1.20 (0.061)	0.14 (0.035)	0.48 (0.048)	1.38 (0.063)	0.16 (0.051)	0.50 (0.064)	1.57 (0.087)	0.13 (0.037)	0.46 (0.037)	1.37 (0.042)
1992	0.16 (0.050)	0.37 (0.056)	1.28 (0.073)	0.20 (0.032)	0.50 (0.039)	1.43 (0.052)	0.19 (0.052)	0.51 (0.057)	1.70 (0.102)	0.19 (0.033)	0.46 (0.033)	1.46 (0.037)

Year	Quantile: 0.1			Quantile: 0.5			Quantile: 0.9			Mean (OLS)		
	Incomplete secondary school	**Complete secondary school**	**Complete tertiary degree**	**Incomplete secondary school**	**Complete secondary school**	**Complete tertiary degree**	**Incomplete secondary school**	**Complete secondary school**	**Complete tertiary degree**	**Incomplete secondary school**	**Complete secondary school**	**Complete tertiary degree**
1993	0.12 (0.068)	0.41 (0.058)	1.20 (0.074)	0.22 (0.030)	0.50 (0.039)	1.50 (0.055)	0.14 (0.055)	0.54 (0.071)	1.75 (0.077)	0.21 (0.034)	0.50 (0.033)	1.50 (0.039)
1994	0.31 (0.082)	0.49 (0.074)	1.28 (0.083)	0.17 (0.036)	0.46 (0.034)	1.45 (0.052)	0.18 (0.048)	0.43 (0.048)	1.70 (0.058)	0.21 (0.033)	0.47 (0.033)	1.47 (0.038)
1995	0.20 (0.059)	0.40 (0.051)	1.18 (0.079)	0.11 (0.029)	0.39 (0.042)	1.38 (0.047)	0.18 (0.061)	0.46 (0.059)	1.65 (0.071)	0.16 (0.034)	0.42 (0.033)	1.40 (0.037)
1996	0.19 (0.049)	0.36 (0.041)	1.11 (0.087)	0.15 (0.033)	0.44 (0.030)	1.37 (0.049)	0.17 (0.063)	0.46 (0.065)	1.77 (0.117)	0.15 (0.042)	0.42 (0.040)	1.42 (0.046)
1997	0.23 (0.062)	0.42 (0.066)	1.08 (0.080)	0.15 (0.043)	0.42 (0.037)	1.34 (0.038)	0.17 (0.093)	0.47 (0.073)	1.59 (0.195)	0.15 (0.051)	0.41 (0.049)	1.35 (0.055)

Note: Standard errors are bootstrapped standard errors, computed with one hundred replications.

Table III. Conditional quantiles

Dependent variable: logarithm of monthly wage earnings (20-to-29-years-of-experience group)

Year	Incomplete secondary school	Complete secondary school	Complete tertiary degree	Incomplete secondary school	Complete secondary school	Complete tertiary degree	Incomplete secondary school	Complete secondary school	Complete tertiary degree	Incomplete secondary school	Complete secondary school	Complete tertiary degree
	Quantile: 0.1			Quantile: 0.5			Quantile: 0.9			Mean (OLS)		
1982	0.24 (0.065)	0.54 (0.122)	1.10 (0.146)	0.24 (0.039)	0.59 (0.065)	1.30 (0.104)	0.44 (0.080)	0.88 (0.161)	1.78 (0.197)	0.26 (0.044)	0.64 (0.051)	1.29 (0.074)
1983	0.36 (0.080)	0.65 (0.084)	1.33 (0.141)	0.24 (0.048)	0.65 (0.064)	1.39 (0.101)	0.23 (0.074)	0.66 (0.132)	1.67 (0.134)	0.29 (0.043)	0.67 (0.056)	1.46 (0.069)
1984	0.22 (0.088)	0.59 (0.081)	1.43 (0.162)	0.25 (0.045)	0.59 (0.062)	1.46 (0.087)	0.24 (0.069)	0.64 (0.096)	1.62 (0.128)	0.28 (0.045)	0.65 (0.053)	1.51 (0.075)
1985	0.22 (0.071)	0.68 (0.130)	1.28 (0.171)	0.23 (0.043)	0.60 (0.071)	1.32 (0.083)	0.21 (0.063)	0.68 (0.097)	1.25 (0.153)	0.24 (0.044)	0.66 (0.054)	1.32 (0.077)
1986	0.36 (0.083)	0.75 (0.098)	1.25 (0.210)	0.34 (0.048)	0.71 (0.082)	1.55 (0.121)	0.35 (0.068)	0.93 (0.067)	1.67 (0.112)	0.36 (0.049)	0.80 (0.055)	1.51 (0.081)
1988	0.32 (0.098)	0.75 (0.103)	1.65 (0.287)	0.22 (0.068)	0.65 (0.067)	1.47 (0.106)	0.21 (0.109)	0.80 (0.110)	1.49 (0.130)	0.27 (0.054)	0.70 (0.057)	1.46 (0.085)
1989	0.25 (0.111)	0.64 (0.163)	1.45 (0.120)	0.25 (0.061)	0.73 (0.095)	1.29 (0.089)	0.15 (0.101)	0.80 (0.157)	1.48 (0.121)	0.22 (0.058)	0.74 (0.065)	1.39 (0.075)
1991	0.16 (0.114)	0.52 (0.134)	1.58 (0.213)	0.21 (0.061)	0.63 (0.065)	1.42 (0.095)	0.24 (0.110)	0.83 (0.104)	1.74 (0.166)	0.22 (0.056)	0.71 (0.059)	1.49 (0.076)
1992	0.27 (0.080)	0.60 (0.116)	1.34 (0.120)	0.20 (0.078)	0.58 (0.066)	1.29 (0.120)	0.09 (0.081)	0.54 (0.103)	1.62 (0.103)	0.23 (0.055)	0.60 (0.058)	1.39 (0.073)

	Quantile: 0.1			Quantile: 0.5			Quantile: 0.9			Mean (OLS)		
Year	**Incomplete secondary school**	**Complete secondary school**	**Complete tertiary degree**	**Incomplete secondary school**	**Complete secondary school**	**Complete tertiary degree**	**Incomplete secondary school**	**Complete secondary school**	**Complete tertiary degree**	**Incomplete secondary school**	**Complete secondary school**	**Complete tertiary degree**
1993	0.33 (0.096)	0.55 (0.087)	1.33 (0.106)	0.16 (0.061)	0.49 (0.086)	1.38 (0.145)	0.14 (0.080)	0.66 (0.071)	1.80 (0.118)	0.21 (0.054)	0.55 (0.057)	1.51 (0.076)
1994	0.39 (0.115)	0.70 (0.099)	1.42 (0.147)	0.28 (0.067)	0.62 (0.074)	1.50 (0.097)	0.27 (0.097)	0.69 (0.100)	1.68 (0.105)	0.32 (0.053)	0.70 (0.055)	1.56 (0.069)
1995	0.37 (0.096)	0.79 (0.092)	1.53 (0.167)	0.30 (0.071)	0.65 (0.072)	1.48 (0.095)	0.22 (0.099)	0.66 (0.118)	1.70 (0.084)	0.31 (0.056)	0.68 (0.058)	1.54 (0.069)
1996	0.53 (0.099)	0.69 (0.099)	1.28 (0.229)	0.38 (0.068)	0.76 (0.082)	1.53 (0.138)	0.37 (0.130)	0.69 (0.113)	1.79 (0.203)	0.43 (0.074)	0.75 (0.075)	1.64 (0.089)
1997	0.14 (0.104)	0.48 (0.088)	1.17 (0.108)	0.26 (0.072)	0.73 (0.073)	1.53 (0.088)	0.24 (0.104)	0.61 (0.104)	1.92 (0.257)	0.19 (0.064)	0.65 (0.067)	1.53 (0.079)

Note: Standard errors are bootstrapped standard errors, computed with one hundred replications.

Table IV. Equality test for conditional quantiles

Year	Incomplete secondary school	Complete secondary school	Complete tertiary degree	Incomplete secondary school	Complete secondary school	Complete tertiary degree	Incomplete secondary school	Complete secondary school	Complete tertiary degree
	PE 0-5			PE: 6-19			PE: 20 -29		
1982	1.31 0.2716	0.56 0.5711	1.13 0.3232	0.12 0.8890	3.15 0.0431	7.65 0.0005	3.06 0.0473	1.70 0.1843	4.42 0.0123
1983	0.27 0.7631	0.75 0.4749	3.83 0.0223	0.65 0.5240	3.18 0.0419	10.58 0.0000	1.46 0.2325	0.01 0.9870	2.78 0.0625
1984	0.05 0.9483	2.13 0.1203	2.86 0.0585	0.32 0.7267	2.88 0.0564	4.51 0.0112	0.09 0.9095	0.14 0.8674	0.65 0.5248
1985	0.27 0.7673	0.08 0.9263	2.89 0.0565	0.10 0.9032	1.15 0.3174	6.77 0.0012	0.03 0.9708	0.40 0.6731	0.16 0.8500
1986	0.51 0.5993	0.88 0.4149	2.04 0.1316	0.62 0.5386	4.13 0.0162	1.90 0.1493	0.05 0.9474	3.35 0.0355	2.04 0.1312
1988	0.09 0.9095	0.66 0.5164	0.46 0.6303	0.70 0.4980	0.94 0.3905	6.64 0.0014	0.68 0.5069	1.15 0.3184	0.22 0.8037
1989	0.63 0.5311	0.27 0.7670	2.16 0.1174	0.04 0.9599	1.39 0.2502	1.45 0.2353	0.59 0.5566	0.30 0.7445	1.93 0.1458
1991	0.33 0.7185	0.37 0.6943	3.12 0.0455	0.42 0.6598	1.64 0.1935	5.68 0.0035	0.15 0.8611	2.33 0.0978	2.07 0.1275
1992	0.40 0.6699	0.35 0.7052	6.57 0.0016	0.47 0.6259	3.16 0.0428	6.42 0.0017	1.13 0.3232	0.08 0.9253	2.85 0.0585
1993	0.07 0.9313	0.79 0.4557	2.81 0.0611	2.03 0.1310	1.34 0.2628	15.51 0.0000	1.81 0.1638	1.30 0.2721	4.68 0.0096

	Year	1994	1995	1996	1997
PE 0-5	**Incomplete secondary school**	1.42 0.2435	1.04 0.3527	1.77 0.1713	1.18 0.3077
	Complete secondary school	2.01 0.1352	2.36 0.0954	3.95 0.0199	2.06 0.1290
	Complete tertiary degree	4.25 0.0148	4.06 0.0179	3.93 0.0203	1.81 0.1655
PE: 6-19	**Incomplete secondary school**	1.70 0.1838	2.21 0.1095	0.34 0.7116	0.66 0.5159
	Complete secondary school	0.38 0.6833	0.73 0.4816	1.53 0.2170	0.26 0.7707
	Complete tertiary degree	10.54 0.0000	11.06 0.0000	12.25 0.0000	6.74 0.0012
PE: 20 -29	**Incomplete secondary school**	0.37 0.6903	0.68 0.5089	1.11 0.3307	0.52 0.5920
	Complete secondary school	0.42 0.6589	0.95 0.3867	0.36 0.6960	3.60 0.0279
	Complete tertiary degree	1.51 0.2219	1.99 0.1371	1.32 0.2689	5.71 0.0035

Note: Statistic of contrast and associated P-Values.

CHANGES IN THE PANAMANIAN WAGE STRUCTURE: A QUANTILE REGRESSION ANALYSIS

SEBASTIÁN GALIANI AND ROCÍO TITIUNIK

SUMMARY

JEL Classification: J30 and J31.

The changes in the wage structure of a country are an important area of research. However, the empirical evidence about the evolution of wages in developing countries is still quite scant. In this paper we contribute to fill this gap by studying the evolution of the wage structure in Panama for the period 1982-1997. We model the (conditional) distribution of wages by means of the quantile regression technique and apply this model to study the male wage distribution and its evolution during the last two decades in Panama. Overall, we find that the wage structure remained fairly stable over the period studied.

Keywords: Wage differentials, wage inequality and quantile regression.

RESUMEN

Clasificación JEL: J30 y J31.

Los cambios en la estructura salarial de un país es un área importante de investigación. Sin embargo, la evidencia empírica sobre la evolución de salarios en los países en desarrollo aún es escasa. En este artículo, intentamos contribuir a esta brecha al estudiar la evolución de la estructura salarial en Panamá para el período 1982-1997. Modelamos la distribución (condicional) de los salarios usando la técnica de regresión por cuantiles y aplicamos este modelo para estudiar la distribución del salario de los hombres y su evolución en Panamá durante las últimas dos décadas. Encontramos que la estructura salarial permaneció relativamente estable en el período considerado.

Palabras claves: Diferenciales salariales, desigualdad salarial y regresión por cuantiles.