# Informal Employment in Bolivia: A Lost Proposition?

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## Abstract

We study participation and relative earnings in the formal, informal, and self-employed sectors in Bolivia. We estimate quantile earnings equations corrected for self-selectivity to address potential biases in the estimates of relative earnings gaps due to the endogeneity of sector participation. Selectivity is significant in all three sectors for all three years studied. The benefits of being more formal like at low quantiles of the informal sector vanish from 1997 to 2002 as the availability of formal jobs decreases. The human capital model is very well fit for 1993 and 1997. In 2002 it is best fit for the formal sector where education and experience explain much of a worker's earnings, and worst fit for the self-employed sector where education does not play a role and experience is only important at high quantiles. We exploit the semi-parametric nature of quantile regression to link the conditional returns to worker characteristics, obtained from the quantile regressions, with the poverty status of households to determine the extent to which unobserved earnings determinants interact with observed characteristics to penalize non-formal workers in poor households. We find that females in non-formal employment suffer the largest penalties. In unreported results (available from the authors upon request) we perform a counterfactual analysis of conditional earnings by sector, decomposing the earnings gaps into differences in endowments of skills and differences in returns to skills. The results suggest segmentation between the formal and informal sector at the lowest conditional quantiles, while higher productivity workers seem to have a choice of which sector to work in.

**KEYWORDS**: earnings gaps, sample selection, quantile regression, multiple-choice models.
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# 1 Introduction

Bolivia has one of the highest levels of informal employment in Latin American and the Caribbean. The informal economy (the salaried micro-enterprise and self-employed sectors) comprised 68% of the remunerated urban employment in 2002 and over three fourth of jobs for households in the two poorest quintiles. Since the poor derive most of their income from labor assets the inability of the Bolivian economy to generate sufficient formal sector jobs is often cited as a central factor underlying the high and persistent poverty in the country.

In the traditional view the informal sector is seen as the repository of jobs for less-advantage workers rationed out of a superior formal sector, mainly as a result of an overly regulated labor market. However, mounting research in the region has questioned this view (see Maloney, 2003). Workers in the informal economy exhibit great heterogeneity. An important fraction of informal jobs may reflect the voluntary choice of workers given their preferences, skills, competing earnings prospects and job characteristics. In Bolivia, about 44% of employment in the top earnings quintile is informal salaried or self-employed. For many of these the view of an incipient entrepreneur sector with potential for productivity growth may be more conforming.

This article analyzes the profile of informal salaried and self-employed urban workers in Bolivia as well as the factors underlying differences in their labor market performance compared to formal sector workers located throughout the entire earnings distribution. We look for characteristics that can cause informal and self-employed workers to perform better than their formal counterparts. We examine the role played by the unobserved (unmeasured) heterogeneity of households and individuals in determining labor market performance. To this aim, we estimate semi-parametric quantile Mincer models corrected for potential selectivity in the sorting of workers across sectors. We capture heterogeneity in the returns to characteristics throughout conditional quantiles of the earnings distribution and relate it to the poverty status of workers (their position in the unconditional per capita household income distribution). This allows us to identify the individual characteristics or specific determinants of the wage structure of the different sectors which most contribute to lower earnings for the poor.

Our focus is on better understanding, among workers participating in urban labor markets, the differences between those who find jobs in growing sectors and those lagging behind, paying particular attention to the role played by their unobserved attributes. This knowledge is important to design public policies to better integrate informal workers to the mainstream economy and enhance social protection schemes.

Our results suggest that simplistic segmented market stories are generally at odds with the observed variety of wage patterns in Bolivia. Our findings conform to two tiers of informality. The lower seemingly consists of workers with a sizable wage disadvantage, and the upper comprises those with more dynamic earnings, some times higher (conditionally) than formal earnings. The unobserved characteristics that give an earnings advantage appear to be biased against poor households, particularly among the female self-employed. Although the disadvantaged informal salaried still lag behind, often they and the self-employed appear at the front line of earnings gains. The flow of workers to informal salaried jobs, particularly those who end up in the lower wage informal jobs, may be viewed as consistent with the relatively better prospects of wage growth in the sector.

The paper is organized as follows. Section 2 discusses definitions and the data for the three sectors and years studied. In Section 3 we describe the econometric methods used in our analysis. Section 4 contains the empirical results, and Section 5 concludes.

# 2 The Informal Economy in Bolivia

## 2.1 Data and Definitions

We use data from the Bolivian 2002 household survey (MECOVI), the 1997 labor force survey and the 1993 household survey (prior to MECOVI) conducted by the National Institute of Statistics (INE). Our analysis focuses on workers 15 to 65 years of age, living in metro areas and receiving cash remunerations.

Since we are primarily concerned with the ability of the informal sector to create good quality jobs, we focus on firm size and distinguish three groups of workers: informal salaried workers (workers in establishments with 1-4 employees plus domestic employees), formal workers (white-collar and blue-collar workers in establishments with 5 or more employees), and the self-employed (those who self classify as *cuenta propia*, employers of micro enterprises, and cooperative workers). Although the self-employed are typically considered part of the informal economy, we treat them as a separate group since they are not subject to the same job relations as salaried workers (they have no boss, no predetermined working hours, etc.).

TABLE 1 reports average characteristics for the three groups in 1993, 1997 and 2002. The informal salaried sector mostly comprises workers in small shops (services and commerce), with no formal contractual arrangement and lacking coverage of benefits such as pensions and health insurance. On average, they are four to nine years younger than formal workers and the self-employed, have 8 years of schooling (3 to 4 fewer than formal workers and about the same as the self-employed) and shorter occupation tenures, and are more likely to still live with their parents. As in most of LAC, the Bolivian self-employed comprise a very heterogeneous sector including from street vendors to small artisans under subcontracting production arrangements. They tend to have higher potential experience[1], the longest tenure in occupation, and a higher fraction wanting to work more hours.

Note the similarities but also some important differences between the informal salaried and self-employed. Both groups work longer hours per week, although the difference decreases for the informal and vanishes for the self-employed in 2002. Also, both groups are disproportionally represented by females (about half) and the indigenous population (44% of the informal and 61% of the self-employed in 2002). However, despite their similar average schooling, the education distribution tends to be more disperse for the self-employed. While a higher fraction of the self-employed have no completed basic education (23% vs. 16% in

[1] To avoid overstating the potential experience of the low educated individuals, we define potential experience as *min {age-education-6, age-14}*.

2002) the share with university education is twice as high than among the informal salaried (8% and 3% in 2002).

Median hourly earnings in 2002 were 70 to 90 percent higher in the formal sector than for the self-employed and informal salaried.[2] Note that total earnings are lower for the informal salaried than for the self-employed, despite working an average of 5 hours more per week. Thus, it is relatively harder to escape poverty through informal employment. During the period of economic boom (1993 to 1997) the self-employed were better off than the informal salaried, but this pattern reverted during the years of recession (1998 to 2002).

However, as stressed in the recent literature, these unconditional average hourly earnings cannot be used as evidence of the superiority of formal sector jobs. First, it cannot be claimed that the lower informal earnings are due to the characteristics of informal jobs rather than to the productive attributes of the workers (both observed and unobserved). One should compare earnings of Bolivian workers with similar characteristics, both observed and unobserved. Second, gaps in average earnings can hardly characterize the situation of workers at all points of the earnings scale. Average earnings gaps may mask the differential situation faced by Bolivians whose unobserved characteristics place them below or above the conditional mean wage function. Third, and more importantly, monetary earnings gaps do not fully capture differences in the quality of jobs across sectors in so far characteristics such as flexible work schedules, the degree of protection and non-monetary benefits (e.g., health insurance, training) are also valued (differently) by individuals. These need to be factored in as part of the cost-benefit choice calculation of workers. We attempt to address these issues below by going beyond narrow average, cross-sectional earnings comparisons and a more careful semi-parametric, multivariate analysis of earnings equations corrected for selectivity.

We next compare the entire unconditional earnings distributions for formal, informal salaried workers and the self-employed (FIGURE 1A). It is clear that median earnings mask substantial disparities between workers at different points of the earnings scale. The distribution for formal sector workers is further to the right of the informal salaried reflecting their wage advantage at any wage level, and in fact, the distributions separate further at the right tail-- earnings gaps are larger between workers at jobs with higher pay. Meanwhile the formal salaried distribution joins the self-employed distribution at the right tail. A worker at the 0.10 quantile of the distribution for the formal salaried (whose wage places him/her above 10% of formal workers) earns about 122 percent more than a worker at the 0.10 quantile of the distribution of the self-employed in 1993. The earnings gap is then reduced to 33 percent for the self-employed at the 0.90 quantile and goes to zero as we move to higher quantiles (the highest paid self-employed earn wages similar to the highest paid formal employees).

These earnings gaps in part arise from differences in productivity-related characteristics of workers. We estimate (but do not report) the gaps for workers at different points of the sector-specific wage distributions conditioning on observed factors and adjusting for differences in sector participation, that is, the earnings distributions that would result if workers had the same set of measured characteristics and worked in a different sector.

[2] Log of hourly earnings are calculated from all reported labor earnings from the main job (net salary plus indirect salaries and benefits) and the number of hours worked in the previous week.

## 2.2 A Primer on Quantile Regression

We use quantile regressions (Koenker and Bassett, 1978) to estimate earnings and return gaps between formal and informal workers at different points of the conditional earnings distribution. Just as least squares models the mean of the distribution of the dependent variable *Y* conditional on the regressors *Z*, quantile regressions give models for different percentiles of this distribution. The $\tau$-th quantile of *Y* conditional on *Z* is given by:

$$Q_\tau\left(Y_i | Z_i\right) = Z_i' \phi(\tau)$$

where the coefficient $\phi(\tau)$ is the slope of the quantile line giving the effect of changes in Z on the $\tau$-th conditional quantile of *Y*. Estimation for different quantiles ($\tau$ from 0 to 1) yields regression lines for various percentiles of the conditional distribution of *Y* such that at least a $\tau$ proportion of regression residuals are below the estimated regression line and approximately a (1-$\tau$) fraction are above it. For instance, median regression ($\tau$ = 0.5) splits the sample in half (half of the residuals above and below the regression line) and gives the same results as ordinary least squares when the distribution is symmetric.

FIGURE 1B captures the basic intuition of our approach. We compute the difference in the intercepts and education coefficients from the estimated quantile Mincer functions for formal and informal workers located at the *same* quantile of the conditional distribution of each sector. Thus, we examine:

$$Q_\tau\left(\ln w_f | e, X\right) - Q_\tau\left(\ln w_i | e, X\right) = \left(\alpha_f(\tau) - \alpha_i(\tau)\right) + \left(\beta_f(\tau) - \beta_i(\tau)\right)\, e + \left(\theta(\tau) - \theta(\tau)\right)\, X$$

Quantile coefficients have the usual regression interpretation. For example, taking $\tau$ = 0.9, $\alpha_f(0.9) - \alpha_i(0.9)$ (the distance A-A') gives the sectoral gap in the level of wages for uneducated workers at the 90th quantile of the conditional wage distribution of each group, that is, the difference between the wage floor of the best paid 10% of uneducated formal and the wage floor of the top 10% of uneducated informal (for any given *X*). Similarly, $\alpha_f(0.1) - \alpha_i(0.1)$ measures the adjusted wage gap at the 10th quantile of the conditional distributions (distance C-C'). Meanwhile $\beta_f(0.9)$ is the slope of the Mincer regression line fitted through the 90th conditional quantiles, and as is conventional refers to the return to education at this quantile. It gives the percentage change in the wage floor of the best-paid 10% of formal workers (within each observed skill level) from an additional year of schooling. Thus, $\beta_f(0.9) - \beta_i(0.9)$ gives the gap in the returns to education between formal and informal workers at this quantile.

In the case of dummy variables, each coefficient measures the log earnings difference between a worker with the particular characteristic (e.g., secondary education) and an otherwise similar worker with the excluded category (e.g., basic education) at the *same* conditional quantile. The anti-log of the coefficients (minus 1) give the relative (adjusted) earnings percentage gap of high school workers with respect to those with only basic education at each given quantile.

For example, the college education dummy for the 10th percentile ($\tau = 0.1$) gives the income per capita gap between households with less than basic and college educated workers located at the 10th percentile of the conditional income distribution, that is, the difference between the earnings floor of the bottom 10 percent of college educated workers and the floor of the bottom 10 percent of workers with less than basic education (controlling for other explanatory characteristics). Similarly, the coefficient at the 50th percentile measures the college earnings premium at the median earnings of the two conditional distributions. In the case of continuous regressors, the coefficient measures the conventional slope of the regression line fitted through a given conditional quantile. It is important to stress that this interpretation pertains to a conditional analysis where confounding effects on income per capita arising from the correlation of the various household characteristics are being isolated.

We can think of bottom conditional quantiles as pertaining to workers with wages lower than granted by their education, experience level and other measured wage determinants, and the upper quantiles to workers with wages higher than predicted by observed skills. The relative positioning of workers in the conditional wage distribution can be related to differences in "ability", which may include a worker's labor market connections, family human capital, school quality, and/or work ethics (Arias, Hallock and Sosa, 2001). The interplay of this unobserved heterogeneity with each regressor results in regression coefficients that vary across quantiles

# *3 Econometric Approach*

Quantile Mincer earnings equations (Koenker and Bassett, 1978) and multinomial choice models are estimated by a two-stage procedure (Fitzenberger, 2003 and Buchinsky, 1998). We use a similar approach to the one proposed by Fitzenberger (2003) for multiple choice sample selection models and quantile regression. In the first stage we determine the probability of participation in the formal/informal/self-employed sectors. In the second stage, we correct sector-specific earnings equations for selection bias, caused by unobservable characteristics that cause participants to join a sector even when they have a low probability of being in that sector.

## 3.1 Selectivity in Quantile Regression

There are few approaches available in the literature for selectivity correction in quantile regression. The method developed by Buchinsky (1998) allows for first-stage semi-parametric estimation of the participation equation using Ichimura’s (1993) SLS estimator. He derives the small sample properties of the second-stage quantile regression estimator for the case when one accounts for sample selection by including a polynomial expansion in the inverse Mill’s ratio in the quantile models. This methodology does not rely on parametric assumptions about the residuals neither in the first nor in the second-stage estimations. However, only *binary* choice models can be estimated in the first-stage.

Also adopting a two-stage approach, Fitzenberger (2003) makes use of a methodology that accommodates polychotomous choice problems in the first-stage participation equation. He estimates linear probability models using seemingly unrelated regressions (SUR) for a three choice model (full-time/part-time/non-employment). In the second-stage quantile wage equations, he uses a second order polynomial expansion in the estimated probabilities to correct for selectivity. Finally, lacking the analytical derivation of the covariance matrix of the coefficients, he bootstraps the standard errors.

We employ a two-stage method in which we estimate the first-stage participation decision with a multinomial logit. This does not free us from making parametric assumptions on the first-stage residuals; however, it does allow us to consider simultaneity in the choice of sector. We rely on $\sqrt{n}$-consistency of the first-stage estimator and on identification assumptions as in Newey (1988). In the second-stage quantile Mincer equations, we include a polynomial expansion in the multinomial equivalent of the inverse Mill's ratio and bootstrap the standard errors.

### 3.1.1 *Why Correct for Selectivity Bias?*

Selectivity bias plays an important role in the estimation of wage equations in the formal, informal salaried, and self-employed sectors. Without correction, biased estimates of important variable such as education may be obtained. For example, a worker with characteristics typical of a formal worker (a high level of education, perhaps) has a low probability of working in the informal sector. However, if such a worker does choose to work in an informal job it is likely because an excellent offer was made (remember, small firms may still be highly productive). Without correcting for selectivity, the estimates of the return to this formal-like workers level of education would be biased upward, in the informal sector. Since we correct for selectivity, this effect would appear as a positive coefficient for the term $\lambda_{i,f}$ (as observed in 1993 and 1997) and the education coefficient would remain unbiased.

## 3.2 Two-stage Estimation

The variable that indicates the sector in which worker $i$ is employed, $I_i$, takes the values: 1 for the formal, 2 for the informal, and 3 for the self-employed sector. For this multinomial choice model we have the following equations for the latent indices:

(1) $$I^*_{si} = z'_i\gamma_s + \eta_{si},$$

where $s = 1,2,3$ specifies the sector and $i = 1,2,\dots,N$ specifies the observation. The employment sector is determined by:

(2) $$I_i = s \quad \text{iff} \quad z'_i(\gamma_s - \gamma_j) > \eta_{ji} - \eta_{si} \quad \text{for all } j \neq s.$$

We assume that $\eta_s$ are independently and identically distributed within the sector (but not between sectors), with the type I extreme-value distribution. This assumption allows the estimation of $\gamma_s$ via maximum likelihood multinomial logit estimation. To estimate the multinomial logit, we must choose the base category for which the coefficients are set to zero. We choose to exclude the formal sector, which implies $\gamma_1 = 0$.

Following Maddala (1983, Section 9.5), if one writes a mean wage equation for sector 1 as $y_{1i} = x'_i\beta_1 + u_{1i}$, the selection bias induced by the fact that $y_{1i}$ is only observed when $I_i = 1$ can be corrected. This correction requires assumptions about the covariance between the residuals from the multinomial logit and the residuals from the wage equation, which we do not discuss here (see Maddala, 1983). First define $\omega_{ij} \equiv \eta_j - \eta_i$ which have the multivariate logistic distribution, and $t_{ij} \equiv z'(\gamma_i - \gamma_j)$ such that the inequalities in equation (2) become $\omega_{sj} < t_{sj}$. The expectation of the wage equation can then be written as:

(3) $$E(y_1 \mid \omega_{1j} < t_{1j}) = x'\beta_1 + \sum_{j=2}^{3} \lambda_j f_j(t_{12}, t_{13}),$$

where $f_j(\cdot)$ can be calculated explicitly (see Maddala, 1983).

Here, we consider quantile wage equations for the various sectors, $s$:

(4) $$Quant_\tau(y_s \mid x = x_i) = x_i'\beta_{s\tau} + u_{s\tau i} = x_i'\beta_{s\tau} + h_{s\tau}(I_{2i}^*, I_{3i}^*) + \varepsilon_{s\tau i},$$

where $x$ is a subset of $z$, and $Quant_\tau(u_{s\tau} \mid x = x_i, I = s) \neq 0$, leading to biased estimates of $\beta_{s\tau}$ if we do not correct for selectivity. However, the inclusion of the term

(5) $$h_{s\tau}(I_{2i}^*, I_{3i}^*) \equiv Quant_\tau(u_{s\tau} \mid z = z_i, I = s)$$

in the wage equation allows unbiased estimates of $\beta_{s\tau}$ since $Quant_\tau(\varepsilon_{s\tau} \mid z = z_i, I = s) = 0$, by definition. This term includes information about the unobservable characteristics of workers that affect their choice of sector to work in (note the conditionality on $z$ and not $x$).

Unfortunately, we have no closed form for $h_{s\tau}(I_{2i}^*, I_{3i}^*)$ and we must resort to approximations. We follow Fitzenberger (2003) and Buchinsky (1998) and approximate $h_{s\tau}(I_{2i}^*, I_{3i}^*)$ by a power series whose coefficients are to be estimated by the regression. We choose to expand in linear terms of the functions $f_j(\cdot)$ in equation (3). In particular,

(6) $$h_{s\tau}(t_{sj}, t_{sk}) \approx \lambda_{s\tau} + \lambda_{s\tau j} f_{s,j} + \lambda_{s\tau k} f_{s,k}$$

where $s \neq j,\ s \neq k,\ j < k$. Our restriction to linear terms is made based on cross-validation techniques which demonstrate the worsening of the model´s fit as higher order terms are included, or if no selectivity is included at all (Newey, Powell and Walker, 1990; and Newey 1988). Newey (1988) and Buchinsky (1998) show that the second stage estimates are consistent if the first stage estimates are.

For clarity we discuss these functions for the formal sector. The function $f_{1,2}$ is the multinomial equivalent of the inverse Mill's ratio. It increases monotonically as the probability of being informal increases. It therefore has very small values when the probability of being self-employed or formal is high. Meanwhile $f_{1,3}$ represents the same for increasing probabilities of self-employment. If $\lambda_{1,2}$ is positive it indicates that individuals with more informal like characteristics that still join the formal sector receive a premium for joining. The coefficient $\lambda_{1,3}$ has a similar interpretation for individuals with more self-employed like characteristics that still are part of the formal sector. Finally, we obtain the standard errors for $\beta_{s\tau}$ by bootstrapping.

### 3.3 Linking Poverty and Conditional Quantiles

As discussed above, quantile regression estimates address heterogeneity in the conditional earnings distribution. We would like to link these conditional returns to workers' positions in the unconditional per capita household income distribution. To do this we first identify the conditional quantile of each worker.

We perform quantile regressions at the 0.05, 0.15, ... , 0.95 quantiles and then identify at which quantile each worker had the smallest residual. Mathematically, the conditional quantile of worker *i* in sector *s*, given by $\theta_i$., is determined by $\theta_i = \arg\min_{\tau}(\varepsilon_{s\tau i})$ where $\tau = 0.05, 0.15, 0.25, \ldots, 0.95$. This allows us to identify the returns to characteristics received by each individual, $\beta_{s\theta_i}$, as well as the returns they would receive at the same conditional quantile in another sector, *j*, ($\beta_{j\theta_i}$) and therefore the penalty (or benefit) that they receive for each of their characteristics by not working in the formal sector, $P_{\beta i} = \beta_{s\theta_i} - \beta_{1\theta_i}$.

Given the sector penalty, $P_{\beta i}$, and the unconditional quintile of per capita household income, $C_i$, for each worker, we regress the penalty on indicator variables of the unconditional quintiles. The regressions are weighted by the inverse of the square of the standard errors from the quantile regression estimations. The regression sample is composed of non-formal workers only, since formal workers have penalties equal to zero. This exercise allows us to determine if poorer households are more severely hurt by participation in the informal or self-employed sectors and which characteristics are most damaging.

## *4 Empirical Findings*

Because the main focus of this version of the paper is on the econometric methods, such as selectivity correction for multinomial choice models in quantile regression and the link between conditional returns and unconditional earnings through quantile regression, we only present the most important results. We have estimations for 1993, 1997 and 2002 and in some cases we may show results just for one year, being the others being available upon request.

### 4.1 Probability Model

We model the participation decision of individuals to engage in the formal, informal or self-employment sector using a multinomial logit model. We choose selection (identifying) variables that may affect the decision to participate in a given sector and not affect the earnings received in that sector. Both the probability model and the earnings equation model include: potential experience (and squared); experience in occupation (and squared); indicator variables for levels of education basic, primary, secondary, technical and university[3]; dummies for ethnicity and female; an indicator for individuals who work less than 20 hours per week; dummies for sector of activity (with commerce as the excluded category) and department (La Paz is the excluded category). The probability model is further identified by

[3] The category less than basic represents years of education $\leq$ 4; basic represents 5$\leq$years of education $\leq$7; and primary indicates 8$\leq$years of education$\leq$11. The definition of secondary, technical and university depends on the type of education attainment.

the inclusion of the following variables: indicators for marital status and school attendance, an indicator for head of household and interaction with female; number of kids less than 15; number of kids less than 6 interacted with female; number of elderly in the household interacted with female; an indicator for living with working parents; other family per capita monthly income (divided by 1000); an indicator for other household member working in the formal sector; and indicators for wanting (and not) and being able (and not) to work more, with the excluded category being not wanting and not being able to work more. This model specification varies a little throughout the analyzed years due to availability of the variables.

The results for the multinomial model for 1993 are presented in TABLE 2C. We use the formal sector as the comparison group and report *relative risk ratios*. Experience enters the model both linearly and quadratically and therefore it is a little tricky to interpret. When it is significant, potential experience[4] decreases the probability of being informal relatively to formal, but it increases the probability of being self-employed. The effect of occupation specific experience (years in occupation) also depends on the evaluation point[5]. Years in occupation have a weaker effect on the probabilities of being informal (negative) and self-employed (positive).

Education attainment decreases the probability of being both informal and self-employed. In 1993, having primary or higher levels of education (compared to the excluded category less than basic) would decrease substantially the probability of informality[6]. In 1993, either basic and primary or technical and university education would reduce the probability of self-employment. The education variables have a stronger negative impact on the participation in the informal salaried sector than on the self-employed sector for all years analyzed.

Belonging to an ethnic group increases substantially the chances of self-employment in 1993, 1997, and 2002, although it is only significant (barely) and negative for the informal salaried in 1993 and 1997. Being a female has a strong, positive and significant effect on the probabilities of informality and self-employment. Being married, however, decreases the chances of informality for all years, while increasing the chances of self-employment (only in 1993). Even though the number of kids less than 15 years old in the family is only significant for the informal in 1993, increasing the probability of informality, having young kids (less than 6 years old) increases the probability of women being self-employed in 1997. It shows that self-employment might be an option for individuals who need flexible working hours. Being the head of household or having another member of the household that is formal increase the probability of formality.

Finally, the surveys ask questions about the willingness and availability to work more hours and they turn to be very important selection variables. If an individual wants and is able to work more hours it increases his chance of being self-employed for all three years, relatively to the excluded category (not wanting and not being able to work more). A similar impact is also found for the informal sector in 1993 and 2002. We also find that the support structure of families, measured by *living with parents* and *other family per capita income* can affect the

[4] Potential experience is only barely significant for the self-employed in 2002 and not significant at all for the informal in 1997.
[5] This variable does not exist in the 1997 survey.
[6] In 1997 and 2002, only educational levels higher than secondary have significant coefficients.

participation decision. Other family per capita income reduces the chances of informality in 1993 and 1997. Living with parents definitely decreases the probability of informality for 1993 and 1997 and of self-employment in 1997.

## 4.2 Quantile Earnings Equations

We proceed with the second-stage estimations, incorporating selectivity polynomials (expansions in the multinomial equivalent of the Inverse Mill's ratio) in the quantile earnings models. TABLE 3C presents the results for the formal, informal and self-employed sectors (at the 10th, 50th and 90th conditional quantiles) in 1993, but an overview of the quantile results for all three years are presented on FIGURES 2A-2C, 3A-3C and 4A-4C. The first thing to observe is that all selectivity polynomials are significant as a group for all quantiles of the formal sector in 1993, the 10th and the 50th in 1997 and the 10th and the 90th in 2002, indicating that unobservable characteristics are relevant in determining earnings in this sector. Beyond this, formal specification tests (Newey, Powell, and ...., 1990) demonstrate that the coefficients from the quantile regressions would be biased if one did not correct for selectivity (*i.e.* the null hypothesis of no change in coefficients between the models with and without selectivity correction is rejected). The selectivity polynomial is not significant at the 10th quantile of the informal sector in 1997 and 2002, nor at the 90th quantile in 2002. It is also not significant at any quantile in 2002, nor at the 90th quantile in 1993 for the self-employed sector.

### *4.2.1 Analysis of Selectivity*

In the formal sector, the individual coefficients of the selectivity polynomial can be interpreted as follows. The coefficients of *lambda.f.i* (coefficient of $\lambda_{1,2}$) are negative and significant and *lambda.f.se* (coefficient of $\lambda_{1,3}$) are positive and significant for all quantiles of 1993 and the 90th quantile of 2002. This indicates that as a worker's probability of being formal decreases (while still being formal), unobservables will cause her to earn less than expected based on her observed level of human capital (wage equation characteristics) if she has more informal like characteristics (negative selection). However, she will make more than expected if she has more self-employed like characteristics (positive selection). This suggests that the opportunity cost for a worker with informal like characteristics to work in the informal sector instead of the formal sector is reduced by the effect of unobservables in 1993, whereas the opposite holds for a worker with self-employed like characteristics. However, in 2002, this trend is nearly reversed at the 10th quantile as *lambda.f.i* becomes large and positive while *lambda.f.se* becomes large and negative. The maintained sign at high quantiles and the reversal of sign at the 10th quantile for the *lambda.f.se* term suggests that workers with self-employed like characteristics include both high ability entrepreneurs and, increasingly since the start of the period of economic stagnation, low ability workers. The change in sign of the *lambda.f.i* term at the 10th quantile from negative to positive and nearly significant suggests that the lowest productivity formal workers with informal like characteristics left (or were forced to leave) the sector, thereby causing the positive selection bias at low conditional quantiles.

For the self-employed, the first reported coefficient is *lambda.se.f* (coefficient of $\lambda_{3,1}$) and it is always positive when significant as the second *lambda.se.i* (coefficient of $\lambda_{3,2}$) is always negative when significant (1993 and 1997). This means that it is advantageous to look more formal like than informal like in the self-employed sector. This corroborates the idea that the self-employed sector is made up of well performing risk taking entrepreneurs who are positively selected into the sector (those with formal-like characteristics) and those who are unable to find any other job and are forced to set up shops for themselves on the side of the road (those with informal-like characteristics). The coefficients become insignificant in 2002, although the signs remain the same with only slightly smaller magnitude, suggesting that the shifts in sector composition from 1997 to 2002 placed some formal-like workers without the risk taking entrepreneur spirit in the self-employed sector.

One striking result from our analysis of the informal sector is that *lambda.i.f* (coefficient of $\lambda_{2,1}$) goes from being positive and significant in 1993 and 1997 to being negative (though insignificant) at the $10^{th}$ and $90^{th}$ quantiles in 2002. This may indicate that during the boom from 1993 to 1997 when formal jobs were plentiful, workers with formal-like characteristics only accepted those informal jobs which offered the best opportunities, causing positive selection into the sector (remember that firm size is only a proxy for firm productivity). This agrees with the interpretation of *lambda.f.i* given above. However, the reduction of the formal sector from 1997 to 2002 may be driving the loss of this positive self selection as lower productivity workers from the formal sector lose their jobs and move to the informal salaried sector.

The term *lambda.i.se* (coefficient of $\lambda_{2,3}$) is negative and significant only at the $50^{th}$ and $90^{th}$ quantiles in 1993, suggesting a negative selection of self-employed like workers into the informal sector during those years. This coefficient remains negative (though insignificant) at the $10^{th}$ quantile throughout all the years, while becoming large and positive (though insignificant) at the $90^{th}$ quantile in 2002 suggesting that high ability workers with self-employed like characteristics are entering the informal sector.

### *4.2.2 Analysis of the Earnings Equations*

FIGURES 1A, 2A and 3A show plots of some selected quantile regression coefficients for the formal, informal and self-employed sectors in 2002. Returns to potential experience decrease with quantile in all three sectors in 1993. In 1997, returns to experience are steady through quantiles for the formal and self-employed sectors, and it is considerably higher at the 90th quantile of the informal sector. Potential experience is not significant at the 90th quantile of the formal sector in 1993 and 2002, at the 90th quantile of the self-employed in 1993 and 1997, and it is not significant at all for the self-employed in 2002. This may be a result of the many older uneducated workers with exaggeratedly large levels of potential experience in the self-employed sector. Returns to tenure at the occupation play an important role to the self-employed in 1993 and to the informal salaried in 2002, with the largest returns coming in the informal sector and the smallest in the self-employed sector. In 1993 and 1997, education is a significant determinant of earnings in all three sectors, however, in 2002 it only plays a role for the formal sector. The great exception is the returns to university in 1993 and 1997, which increase with quantile and present similar magnitude in all three sectors. Returns to technical education are never significant for the self-employed sector[7] , indicating that investments in this type of education would only benefit formal and informal salaried workers.

[7] It is negative and significant for the 90th quantile of the self-employed in 1993.

One's being ethnic (indigenous) severely hurts in the formal sector, but it does not affect earnings in the informal sector. For the self-employed, penalty for ethnic background is only significant at median and high quantiles in 1993 and low and median quantiles in 1997. Women are severely penalized throughout the self-employed distribution with the worst penalties at the lowest quantiles. In 1993, women also receive lower earnings at the formal and informal sectors, but the penalties are higher at the top of the conditional earnings distribution. In 2002, the human capital model is well fit for the formal sector and poorly fit for the other sectors.

FIGURES 1B, 2B and 3B present the coefficients for the formal, informal and self-employed sectors in 1997. Returns to potential experience vary significantly across quantiles only in the self-employed sector as it becomes insignificant at higher quantiles. The formal and informal sectors receive the highest returns. In the formal sector, returns to basic, primary, and technical education decrease with quantile, while all other returns remain constant. Perhaps one's earnings are capped without a university education or some forms of education substitute for ability, rather than proxy for it. In the informal sector, for all but basic and primary education, the premium is larger at high deciles, becoming larger than the formal premiums for technical and university education. We observe a similar behavior in the self-employed sector for secondary education, though the premiums remain smaller than the formal sector's. In contrast to 2002, education and potential experience are significant determinants of earnings for all sectors, not just the formal one.

In 1997, ethnicity was not penalized in the informal sector. It hurts throughout the formal sector, worsening with increasing quantile, and is penalized at the low quantiles of the self-employed sector. In 2002, the ethnic penalties were not significant at any quantile of the self-employed sector, though they were large and nearly significant at the 90$^{th}$ percentile. Being female is only penalized in the self-employed sector. This penalty does not significantly vary across quantile (unlike 2002 where the penalty decreased with increasing quantile). In the formal sector, there is no female earnings disadvantage in 1997, whereas in 2002 the highest quantiles suffered this penalty. The human capital models were well specified for all sectors in 1997, rather than just the formal as in 2002.

The plots for 1993 are in FIGURES 1C, 2C and 3C. Returns to potential experience vary significantly across quantiles only in the self-employed sector as it becomes insignificant at higher quantiles, as in 1997. Returns to tenure at occupation decrease with quantile in the formal sector and are not significantly different across quantiles in the other sectors. Returns to education, when significant, are constant throughout quantiles for the formal sector, except for university for which the returns increase with quantile. In the informal sector any significant returns to education are constant throughout quantiles. For the self-employed sector, returns to education increase with quantile for technical, secondary, and university education. Ethnicity is penalized: steadily throughout the formal sector (excepting a slight increase at the 90$^{th}$ quantile); increasingly with quantile in the self-employed sector; and not at all in the informal sector. The female earnings disadvantage is steady throughout quantiles of all sectors (with perhaps a slight increase at the 90$^{th}$ quantile of the formal sector) and is largest for the self-employed as in 1997 and 2002.

## 4.3 Linking Poverty and Conditional Quantiles

TABLES 4 through 10 contain the results from the analysis where we link conditional returns and household poverty status. The differences are measured relatively to the formal sector. TABLE 4 shows the penalty for being a non-formal female is much larger in the poorest households throughout all years (-0.169 (16%) in 2002, obtained by summing the constant and the result for quintile 1). TABLE 5 shows the difference in returns to ethnicity (indigenous) in non-formal sectors. In fact, there is a premium for ethnic workers in the informal sector and the poorest households benefit the most. This premium increased from 1993 to 2002.

The remaining figures (7 to 11) treat the differences associated with returns to education. In 2002, among the workers with basic education (21% of informal and 23% of self-employed) only the poorest ones received a weak penalty (around -0.03, see TABLE 6). If we break down the results for the informal salaried and self-employed with basic education, the former receive a premium, while the latter a penalty. This may reflect the effects of the recession in shortening the salaried jobs in 2002. The 1993 and 1997 regressions (TABLE 6) showed a premium for workers with basic education in the informal sector, but the poorest ones benefit the least. For workers with primary education (30% of informal and 23% of self-employed in 2002) there is a small premium for the richest self-employed (0.04, see TABLE 7) and a penalty (-0.16) for the richest informal salaried. In both cases, the poorest ones are more benefited and less hurt, respectively. Small penalties for the poorest households are consistent with the results for 1997 and 1993, however in these years wealthier households received slightly higher relative returns to a primary education in non-formal employment (see TABLE 7). In 2002, 26% of informal workers and 19% of self-employed workers had secondary education. Having secondary education helps the poorest non-formal workers, but hurts the richest ones in 2002 (see TABLE 8). This is in contrast to 1997 and 1993 when poorer households received larger penalties for returns to secondary education in non-formal employment (see TABLE 8).

The remaining educational categories (technical and university) account for only 7% and 12% of the informal and self-employed workers, respectively and tend to be concentrated in the wealthier households. The regressions for 2002 and 1997 show quite large penalties for non-formal technically educated workers (around -0.6 in 2002 and -0.23 in 1997 for the richest ones, see TABLE 9). In 1993 and 1997 the poorest non-formal workers with technical education are worse off than the richest ones (-0.33 and -0.55). Finally, there are huge penalties for university educated workers in the informal and self-employed sectors relative to their formal counterparts in 1997 and 2002 (around -0.8 (55%) in 2002, see TABLE 10). The penalties were a bit smaller for the poorest self-employed in 1997, but the poorest informal salaried with university education were severely hurt in 1997. This may be related to the economic stagnation from 1997 to 2002, which failed, to provide a sufficient number of formal jobs for university educated workers.

In summary, ethnicity is the only characteristic which yields higher returns in the informal sector for poor workers for all years studied. Among the education categories, only primary education benefited the workers in the poorest households in 2002, while in 1997 it is basic education that benefits the poorest non-formal workers. In 1993, basic, primary and secondary education levels provide premiums for the poorest non-formal workers, relative to returns in the formal sector. It is important to point out that those penalties/premiums are calculated based on returns to characteristics, without taking into account the magnitude of the models' intercepts, which could make the conditional earnings gaps behave in a different, sometimes contradictory way.

## 5 Conclusion

Labor participation and earnings follow different patterns in each of the formal, informal and self-employment sectors in urban Bolivia. The choice of self-employment is certainly of some utility for individuals with restricted working hours, such as women with young children, as more than 70% of self-employed workers who work less than 20 hours per week are female. This may explain the lower earnings they are willing to accept for self-employed work. Formal employment is often found by heads of households, individuals in households with other formal employed, and individuals with high levels of other family per capita income, indicating the strong role played by networking in finding a formal job.

Selectivity plays an important role in determining earnings for the three sectors. Our models indicate that if one does not possess typical formal characteristics and still works in the sector; he will earn less than expected based on his observed characteristics. This suggests that there are some specific abilities, which are not being captured by our human capital models that are valued by the formal sector.

A noteworthy finding from our estimations is that the selectivity patterns changed with time. In 1993 and 1997, informal workers with formal-like characteristics were positively selected into the informal sector. In this time period, formal jobs were plentiful and workers with formal-like characteristics only accepted those informal jobs which offered excellent opportunities. By 2002, this positive selection had eroded away and workers with formal-like characteristics were negatively (though insignificantly) selected into the $10^{th}$ quantile of the informal sector. The reduction in the size of the formal sector from 1997 to 2002 may have been responsible by causing lower productivity workers from the formal sector lose their jobs and move to the informal salaried sector. The selectivity estimates from the formal sector confirm this hypothesis. Workers with informal-like characteristics go from being negatively to positively (and nearly significant) selected into the formal sector from 1993 to 2002. Again, this suggests that the lowest productivity formal workers with informal-like characteristics left (or were forced to leave) the sector, thereby causing the positive selection bias at low conditional quantiles.

The formal sector, as expected, is the sector for which the human capital models are best adjusted, specially in 2002. Returns to education are considerably higher in the formal and informal sectors than in the self-employed. Getting an education degree increases yours chances of becoming formal and increases your earnings once you are part of the sector. Education is rather unimportant for earnings determination in the informal and self-employed sectors in 2002, whereas it was much more important in 1993 and 1997.

The worst penalties for poor households from non-formal work are associated with being female for all years. There are also some big penalties for the poor from technical education, but only for 1993 and 1997. Ethnicity provides a small premium for the poor non-formal workers, relative to formal returns, throughout the years. In 2002, the educational penalties are small for basic and primary education and increase for secondary and above, leading us to conclude that the low educated (male) non-formal worker does not receive large penalties from not participating in the formal sector. For those with secondary education the penalties are larger in 2002, but decreasing with income levels, and for those with higher education there are very few observations in poor households, although the penalty for non-formal work is quite high.

## 6 References


Buchinsky, M. (1998). "The dynamics of changes in the female wage distribution in the USA: A quantile regression approach". Journal of Applied Econometrics 13, 1-30.

Fitzenberger, B. (2003). "Gender wage differences across quantiles, accounting for sample selection", mimeo, University of Mannheim

Ichimura, H., (1993). "Semiparametric least-squares (SLS) and weighted SLS estimation of single-index models". Journal of Econometrics, Vol. 58, 71-120.

Koenker, R. and Bassett, G. (1978). "Regression Quantiles", Econometrica, Vol. 46 No.1, pp. 1-26.

Lay, J. (2001). "Segmentation and informality in urban labour markets: evidence from Bolivia and implications for poverty reduction". Kiel Institute of World Economics.

Machado, J. and Koenker, R. (1999). "Goodness of fit and related inference processes for quantile regression", Journal of the American Statistical Association, Vol. 94, pp.1296-1310.

Maddala, G. S. (1983). Limited-dependent and qualitative variables in econometrics, Cambridge University Press, New York.

Maloney, W. (2003). "Informality revisited", World Bank Policy Research Working Paper n. 2965.

Newey, W. (1988) "Two step series estimation of sample selection models", mimeo, Department of Economics, MIT.

Newey, W., J. Powell. and J. Walker (1990) "Semiparametric estimation of selection models: some empirical results", The American Economic Review, vol. 80, no. 2, 324-328.

Tannuri-Pianto, M. and D. Pianto (2002). " Informal employment in Brazil – a choice at the top and segmentation at the bottom: a quantile regression approach", Working paper n 236, Department of Economics, University of Brasilia.

Wodon, Q. (2003). Internal Migration, Urbanization and Poverty: case studies for Latin America, The World Bank, draft.

**TABLE 1- Summary Statistics, 1993, 1997, 2002.** Weighted sample averages.

| Variables | Formal | | | Informal | | | Self-Employed | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1993 | 1997 | 2002 | 1993 | 1997 | 2002 | 1993 | 1997 | 2002 |
| Log hourly earnings | 1.06 | 1.64 | 1.78 | 0.14 | 0.65 | 1.14 | 0.51 | 1.26 | 1.25 |
| Labor earnings month | 460.00 | 800.00 | 1073.34 | 250.00 | 400.00 | 649.96 | 324.75 | 649.50 | 606.20 |
| Hours week | 44.58 | 43.98 | 47.22 | 55.24 | 54.02 | 50.76 | 48.78 | 48.07 | 45.39 |
| Age (years) | 33.41 | 34.72 | 34.49 | 27.66 | 29.74 | 30.32 | 38.82 | 39.17 | 38.90 |
| Pot. Exp. (years) | 14.98 | 16.10 | 15.99 | 12.07 | 13.70 | 14.22 | 22.93 | 23.14 | 22.77 |
| Years Occupation | 6.79 | 6.08 | 6.70 | 4.82 | 3.64 | 4.53 | 8.56 | 8.34 | 8.85 |
| Education (years) | 11.55 | 11.93 | 11.84 | 7.81 | 8.52 | 8.73 | 7.47 | 7.91 | 8.24 |
| Educ. less than basic | 0.10 | 0.08 | 0.08 | 0.21 | 0.18 | 0.16 | 0.30 | 0.26 | 0.23 |
| Educ. basic | 0.12 | 0.10 | 0.11 | 0.29 | 0.23 | 0.21 | 0.23 | 0.22 | 0.23 |
| Educ. primary | 0.17 | 0.17 | 0.19 | 0.27 | 0.26 | 0.30 | 0.19 | 0.23 | 0.23 |
| Educ. secondary | 0.25 | 0.27 | 0.27 | 0.17 | 0.27 | 0.26 | 0.18 | 0.18 | 0.19 |
| Educ. technical | 0.22 | 0.20 | 0.17 | 0.03 | 0.05 | 0.04 | 0.05 | 0.05 | 0.04 |
| Educ. university | 0.14 | 0.18 | 0.18 | 0.02 | 0.02 | 0.03 | 0.05 | 0.06 | 0.08 |
| Ethnic (language) | 0.36 | 0.25 | 0.39 | 0.48 | 0.37 | 0.44 | 0.61 | 0.51 | 0.61 |
| Female | 0.32 | 0.33 | 0.33 | 0.47 | 0.48 | 0.47 | 0.52 | 0.49 | 0.55 |
| Married | 0.63 | 0.64 | 0.68 | 0.41 | 0.40 | 0.50 | 0.76 | 0.77 | 0.76 |
| Less 20 hours week | 0.04 | 0.07 | 0.09 | 0.02 | 0.03 | 0.07 | 0.10 | 0.10 | 0.17 |
| Industry & Agriculture | 0.22 | 0.24 | 0.23 | 0.15 | 0.15 | 0.19 | 0.21 | 0.21 | 0.24 |
| Transport & Utilities | 0.07 | 0.07 | 0.08 | 0.16 | 0.16 | 0.11 | 0.09 | 0.10 | 0.07 |
| Construction | 0.09 | 0.09 | 0.10 | 0.11 | 0.09 | 0.10 | 0.08 | 0.10 | 0.08 |
| Commerce | 0.14 | 0.11 | 0.12 | 0.16 | 0.20 | 0.19 | 0.51 | 0.46 | 0.48 |
| Government & Educ. | 0.32 | 0.30 | 0.27 | 0.01 | 0.02 | 0.02 | 0.00 | 0.00 | 0.01 |
| Services | 0.17 | 0.18 | 0.21 | 0.41 | 0.38 | 0.39 | 0.11 | 0.13 | 0.12 |
| La Paz (capital) | 0.31 | 0.23 | 0.13 | 0.26 | 0.27 | 0.10 | 0.25 | 0.21 | 0.08 |
| Chuquisaca | 0.04 | 0.05 | 0.06 | 0.05 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 |
| La Paz | 0.42 | 0.33 | 0.31 | 0.41 | 0.41 | 0.32 | 0.43 | 0.42 | 0.40 |
| Cochabamba | 0.14 | 0.16 | 0.09 | 0.11 | 0.21 | 0.12 | 0.14 | 0.16 | 0.12 |
| Oruro | 0.05 | 0.05 | 0.06 | 0.05 | 0.03 | 0.03 | 0.06 | 0.07 | 0.05 |
| Potosi | 0.03 | 0.04 | 0.04 | 0.02 | 0.03 | 0.03 | 0.03 | 0.03 | 0.04 |
| Tarija | 0.04 | 0.03 | 0.02 | 0.04 | 0.03 | 0.05 | 0.03 | 0.03 | 0.04 |
| Santa Cruz | 0.27 | 0.32 | 0.38 | 0.28 | 0.22 | 0.39 | 0.25 | 0.22 | 0.28 |
| Beni & Pando | 0.02 | 0.03 | 0.04 | 0.03 | 0.03 | 0.03 | 0.02 | 0.02 | 0.03 |
| Attend school | 0.15 | 0.13 | 0.16 | 0.16 | 0.18 | 0.16 | 0.04 | 0.04 | 0.05 |
| Head HH | 0.50 | 0.54 | 0.58 | 0.33 | 0.34 | 0.37 | 0.51 | 0.54 | 0.52 |
| Head HH * Female | 0.04 | 0.06 | 0.08 | 0.03 | 0.06 | 0.05 | 0.11 | 0.11 | 0.13 |
| N. kids less 15 years | 1.72 | 1.51 | 1.24 | 1.92 | 1.58 | 1.02 | 2.02 | 1.75 | 1.48 |
| N. kids less 6 * Female | 0.20 | 0.15 | 0.13 | 0.29 | 0.24 | 0.15 | 0.38 | 0.28 | 0.28 |
| N. elderly HH * Female | 0.04 | 0.06 | 0.03 | 0.09 | 0.11 | 0.04 | 0.05 | 0.04 | 0.04 |
| Live with parents | 0.28 | 0.26 | 0.16 | 0.29 | 0.33 | 0.21 | 0.11 | 0.10 | 0.08 |
| Want/Able work more | 0.05 | 0.14 | 0.30 | 0.08 | 0.15 | 0.32 | 0.06 | 0.19 | 0.41 |
| Want/Not able | - | 0.04 | 0.06 | - | 0.05 | 0.06 | - | 0.03 | 0.07 |
| Not want/Able | - | - | 0.04 | - | - | 0.03 | - | - | 0.04 |
| Oth.Fam.Inc.(pc/1000) | 0.18 | 0.32 | 0.39 | 0.09 | 0.20 | 0.25 | 0.11 | 0.22 | 0.32 |
| Other HH Formal | 0.45 | 0.46 | 0.39 | 0.38 | 0.33 | 0.29 | 0.27 | 0.28 | 0.24 |
| Sample Size | 2,342 | 1,951 | 835 | 1,240 | 707 | 512 | 2,382 | 1,877 | 1,154 |

*Note*: Median values for "Log hourly earnings" and "Labor earnings month".

**TABLE 2C- Multinomial Logit, 1993. Relative Risk Ratios.**

Formal sector is the comparison group.

| Variables | Informal | | Self-Employed | |
|---|---|---|---|---|
| | RRR | Std.Error | RRR | Std.Error |
| Pot. Exp | 0.934 | 0.016*** | 1.091 | 0.017*** |
| Pot. Exp^2*100 | 1.104 | 0.038*** | 0.908 | 0.028*** |
| Years Occup. | 0.968 | 0.017* | 0.997 | 0.015 |
| Years Occup^2*100 | 1.155 | 0.067*** | 1.100 | 0.054** |
| Basic educ. | 1.027 | 0.152 | 0.773 | 0.103** |
| Primary educ. | 0.679 | 0.105*** | 0.784 | 0.111* |
| Secondary educ. | 0.347 | 0.059*** | 0.853 | 0.129 |
| Technical educ | 0.114 | 0.028*** | 0.398 | 0.079*** |
| University educ. | 0.087 | 0.024*** | 0.642 | 0.135** |
| Ethnic | 1.216 | 0.142* | 1.740 | 0.1778*** |
| Female | 1.941 | 0.331*** | 1.950 | 0.333*** |
| Married | 0.538 | 0.080*** | 1.888 | 0.264*** |
| Less 20 hours week | 0.699 | 0.202 | 5.907 | 1.451*** |
| Industry & Agriculture | 0.538 | 0.082*** | 0.281 | 0.031*** |
| Construction | 2.881 | 0.495*** | 0.425 | 0.066*** |
| Transport & Comun. | 1.010 | 0.187 | 0.281 | 0.043*** |
| Government & Educ. | 0.060 | 0.020*** | 0.001 | 0.001*** |
| Services | 2.232 | 0.325*** | 0.220 | 0.030*** |
| La Paz (capital) | 0.582 | 0.102*** | 0.588 | 0.088*** |
| Chuquisaca | 0.901 | 0.222 | 0.749 | 0.175 |
| Cochabamba | 0.592 | 0.113*** | 0.764 | 0.125* |
| Oruro | 1.000 | 0.247 | 0.811 | 0.173 |
| Potosi | 0.535 | 0.132*** | 0.575 | 0.122*** |
| Tarija | 0.661 | 0.152* | 0.712 | 0.150 |
| Santa Cruz | 0.618 | 0.114*** | 0.809 | 0.130 |
| Beni & Pando | 0.818 | 0.211 | 1.626 | 0.385** |
| Attend. School | 0.687 | 0.104*** | 0.625 | 0.110*** |
| Head HH | 0.600 | 0.112*** | 0.483 | 0.086*** |
| Head HH * Fem. | 0.645 | 0.198 | 2.679 | 0.693*** |
| N. kids less 15 | 1.073 | 0.033** | 1.001 | 0.030 |
| N. kids less 6 * Fem | 0.860 | 0.081 | 1.090 | 0.093 |
| N. Elderly HH * Fem | 1.260 | 0.196 | 0.996 | 0.183 |
| Live with parents | 0.538 | 0.088*** | 0.890 | 0.152 |
| Want/Able work more | 1.880 | 0.360*** | 1.376 | 0.242* |
| Oth. fam. pc income | 0.253 | 0.100*** | 0.653 | 0.196 |
| Oth. HH formal | 0.659 | 0.070*** | 0.488 | 0.049*** |
| F-stat (72, 5892) | 27.13 | | | |
| Prob > F | 0.000 | | | |

Note: 5,964 obs; 898,385 sum of weights. ***, **, * denote significance at 1%, 5% and 10% respectively. La Paz is the excluded department and Commerce is the excluded activity.

**TABLE 3C – Quantile Regression Estimates- 1993, with selectivity correction. (Log Hourly Earnings)**

| | Formal | | | Informal | | | Self-Employed | | |
|---|---|---|---|---|---|---|---|---|---|
| **Variables** | **10%** | **50%** | **90%** | **10%** | **50%** | **90%** | **10%** | **50%** | **90%** |
| Constant | -0.342 | 0.594 | 1.348 | -1.134 | -0.338 | 0.355 | -1.314 | -0.053 | 0.769 |
| | (0.216) | (0.142)* | (0.271)* | (0.168)* | (0.135)* | (0.158) | (0.496)* | (0.245) | (0.489)* |
| λ (f.i) (i.f) (se.f) | -0.550 | -0.495 | -0.563 | 0.415 | 0.453 | 0.442 | 0.828 | 0.716 | 0.292 |
| | (0.159)* | (0.121)* | (0.207)* | (0.177)* | (0.165)* | (0.230)* | (0.240)* | (0.214)* | (0.370) |
| λ (f.se) (i.se) (se.i) | 0.370 | 0.294 | 0.390 | -0.386 | -0.428 | -0.307 | -0.732 | -0.708 | -0.285 |
| | (0.140)* | (0.099)* | (0.206)* | (0.186) | (0.171)* | (0.234)* | (0.246)* | (0.224)* | (0.416) |
| Pot. Experience | 0.025 | 0.018 | 0.019 | 0.049 | 0.049 | 0.036 | 0.021 | 0.018 | 0.008 |
| | (0.009)* | (0.006)* | (0.013) | (0.010)* | (0.008)* | (0.011)* | (0.012)* | (0.011)* | (0.018) |
| Pot. Experience^2 | -0.058 | -0.041 | -0.019 | -0.085 | -0.087 | -0.050 | -0.052 | -0.046 | -0.010 |
| * 100 | (0.020)* | (0.013)* | (0.025) | (0.020)* | (0.015)* | (0.026)* | (0.022)* | (0.020)* | (0.029) |
| Years in Occup. | 0.025 | 0.014 | -0.007 | 0.014 | 0.007 | -0.004 | 0.016 | 0.020 | 0.032 |
| | (0.008)* | (0.006)* | (0.014) | (0.013) | (0.008) | (0.012) | (0.009)* | (0.006)* | (0.010)* |
| Years in Occup^2 | -0.052 | -0.003 | 0.018 | -0.020 | 0.010 | 0.013 | -0.001 | -0.020 | -0.065 |
| * 100 | (0.027) | (0.022) | (0.040) | (0.058) | (0.025) | (0.034) | (0.025) | (0.022) | (0.028)* |
| Basic educ. | 0.121 | -0.039 | -0.094 | 0.093 | -0.004 | -0.040 | 0.297 | 0.151 | 0.192 |
| | (0.100) | (0.078) | (0.112) | (0.070) | (0.052) | (0.079) | (0.076)* | (0.051)* | (0.103)* |
| Primary educ. | 0.119 | -0.039 | -0.066 | 0.132 | 0.011 | -0.064 | 0.221 | 0.173 | 0.350 |
| | (0.105) | (0.077) | (0.106) | (0.094) | (0.060) | (0.084) | (0.107)* | (0.058)* | (0.116)* |
| Secondary educ. | 0.245 | 0.178 | 0.279 | 0.329 | 0.284 | 0.289 | 0.406 | 0.286 | 0.697 |
| | (0.129)* | (0.077)* | (0.110)* | (0.112)* | (0.096)* | (0.127)* | (0.118)* | (0.092)* | (0.185)* |
| Technical educ. | 0.530 | 0.397 | 0.451 | 0.749 | 0.626 | 0.511 | 0.215 | 0.103 | 0.484 |
| | (0.147)* | (0.087)* | (0.115)* | (0.186)* | (0.172)* | (0.215)* | (0.183) | (0.175) | (0.223)* |
| University educ. | 0.925 | 1.024 | 1.218 | 0.907 | 0.839 | 1.240 | 0.881 | 1.095 | 1.417 |
| | (0.156)* | (0.103)* | (0.146)* | (0.235)* | (0.238)* | (0.521)* | (0.218)* | (0.180)* | (0.319)* |
| Ethnic | -0.198 | -0.137 | -0.276 | 0.034 | -0.037 | -0.085 | -0.036 | -0.123 | -0.216 |
| | (0.055)* | (0.044)* | (0.075)* | (0.074) | (0.053) | (0.083) | (0.081) | (0.050)* | (0.091)* |
| Female | -0.102 | -0.124 | -0.265 | -0.206 | -0.237 | -0.252 | -0.335 | -0.336 | -0.317 |
| | (0.063)* | (0.048)* | (0.091)* | (0.094)* | (0.079)* | (0.118)* | (0.095)* | (0.070)* | (0.113)* |
| Married | 0.015 | 0.024 | -0.015 | 0.085 | 0.032 | -0.009 | 0.059 | -0.022 | 0.006 |
| | (0.057) | (0.046) | (0.080) | (0.086) | (0.069) | (0.078) | (0.083) | (0.057) | (0.100) |
| Hours lt 20 | 0.515 | 0.372 | 0.917 | 1.306 | 1.441 | 1.412 | 0.776 | 0.902 | 1.083 |
| | (0.088)* | (0.091)* | (0.263)* | (0.197)* | (0.216)* | (0.329)* | (0.120)* | (0.096)* | (0.145)* |
| Joint test, lambdas | | | | | | | | | |
| $\chi^2$ (2)– *statistic* | 12.97 | 17.75 | 9.34 | 5.40 | 7.49 | 5.54 | 11.70 | 10.96 | 0.71 |
| p - *value* | 0.002 | 0.000 | 0.009 | 0.067 | 0.024 | 0.063 | 0.004 | 0.004 | 0.702 |

*Note:* Standard errors in parentheses. * - denotes significance at 10%.

**TABLE 3C, CONTINUED – Quantile Regression Estimates- 1993, with selectivity correction. (Log Hourly Earnings)**

| | Formal | | | Informal | | | Self-Employed | | |
|---|---|---|---|---|---|---|---|---|---|
| **Variables** | **10%** | **50%** | **90%** | **10%** | **50%** | **90%** | **10%** | **50%** | **90%** |
| Indust. & Agric. | 0.076 | -0.013 | -0.084 | -0.066 | -0.115 | -0.109 | 0.018 | -0.027 | -0.011 |
| | (0.084) | (0.060) | (0.146) | (0.131) | (0.096) | (0.124) | (0.087) | (0.073) | (0.116) |
| Construction | 0.408 | 0.278 | 0.423 | 0.232 | 0.215 | 0.361 | 0.462 | 0.455 | 0.368 |
| | (0.145)* | (0.088)* | (0.194)* | (0.161) | (0.122)* | (0.143)* | (0.138)* | (0.108)* | (0.184)* |
| Transp. & Com. | 0.462 | 0.221 | 0.030 | 0.434 | 0.327 | 0.152 | 0.119 | -0.033 | -0.314 |
| | (0.093)* | (0.068)* | (0.158) | (0.155)* | (0.114)* | (0.123) | (0.124) | (0.088) | (0.146)* |
| Gov. & Educ. | 0.165 | 0.118 | 0.129 | -0.506 | -0.531 | -0.605 | -0.750 | 0.068 | 1.281 |
| | (0.134) | (0.105) | (0.246) | (0.337) | (0.419) | (0.406) | (0.797) | (1.191) | (1.248) |
| Services | 0.324 | 0.296 | 0.445 | -0.169 | -0.277 | -0.182 | 0.126 | 0.142 | 0.067 |
| | (0.107)* | (0.085)* | (0.174)* | (0.157) | (0.121)* | (0.168) | (0.141) | (0.112) | (0.203) |
| La Paz (capital) | 0.076 | 0.089 | 0.196 | 0.124 | 0.214 | 0.110 | 0.285 | 0.178 | 0.303 |
| | (0.082) | (0.059) | (0.111)* | (0.089)* | (0.082)* | (0.093) | (0.098)* | (0.076)* | (0.114)* |
| Chuquisaca | 0.124 | 0.123 | 0.242 | -0.338 | -0.162 | -0.160 | -0.235 | 0.107 | 0.441 |
| | (0.115) | (0.100) | (0.130)* | (0.124)* | (0.115) | (0.114) | (0.188) | (0.122) | (0.210)* |
| Cochabamba | 0.112 | 0.075 | 0.140 | 0.130 | 0.037 | 0.012 | 0.253 | 0.195 | 0.479 |
| | (0.080) | (0.067) | (0.108) | (0.081) | (0.091) | (0.132) | (0.117)* | (0.081)* | (0.147)* |
| Oruro | 0.041 | -0.023 | -0.177 | -0.566 | -0.379 | -0.526 | -0.218 | -0.186 | -0.016 |
| | (0.128) | (0.070) | (0.110) | (0.145)* | (0.088)* | (0.139)* | (0.148) | (0.086)* | (0.184) |
| Potosi | -0.214 | -0.165 | -0.039 | -0.258 | -0.280 | -0.065 | -0.237 | -0.204 | 0.131 |
| | (0.113)* | (0.126) | (0.122) | (0.136)* | (0.111)* | (0.329) | (0.153)* | (0.121)* | (0.178) |
| Tarija | -0.038 | -0.012 | -0.143 | 0.030 | -0.073 | -0.282 | 0.075 | 0.222 | 0.275 |
| | (0.109) | (0.069) | (0.134) | (0.113) | (0.093) | (0.112)* | (0.178) | (0.111) | (0.158) |
| Santa Cruz | 0.180 | 0.164 | 0.169 | 0.317 | 0.263 | 0.077 | 0.809 | 0.607 | 0.630 |
| | (0.084)* | (0.065)* | (0.113)* | (0.100)* | (0.080)* | (0.118) | (0.111)* | (0.074)* | (0.112)* |
| Beni & Pando | 0.192 | 0.197 | 0.044 | 0.186 | 0.090 | -0.151 | 0.607 | 0.511 | 0.365 |
| | (0.158) | (0.080)* | (0.137) | (0.112) | (0.112) | (0.148) | (0.139)* | (0.114)* | (0.139)* |
| N. Obs. | | 2,342 | | | 1,240 | | | 2,382 | |

*Note:* Standard errors in parentheses. * - denotes significance at 10%. *La Paz* is the excluded department and *Commerce* is the excluded activity.

**TABLE 4 – Differences in conditional returns to Female,** relative to the formal sector: by unconditional *per capita* household income quintile.

| | Informal Salaried | | | Self Employed | | | Informal Sector | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1993 | 1997 | 2002 | 1993 | 1997 | 2002 | 1993 | 1997 | 2002 |
| Quintile 1 | -0.019 | -0.104 | -0.260 | -0.012 | 0.004 | -0.116 | -0.026 | -0.011 | -0.200 |
| | (0.011)* | (0.020)*** | (0.034)*** | (0.005)** | (0.006) | (0.023)*** | (0.008)*** | (0.009) | (0.026)*** |
| Quintile 2 | -0.026 | -0.086 | -0.149 | -0.016 | 0.011 | -0.107 | -0.014 | 0.004 | -0.152 |
| | (0.010)*** | (0.019)*** | (0.044)*** | (0.004)*** | (0.005)** | (0.019)*** | (0.008)* | (0.009) | (0.026)*** |
| Quintile 3 | -0.035 | -0.082 | -0.059 | -0.013 | 0.015 | -0.074 | -0.003 | 0.006 | -0.098 |
| | (0.010)*** | (0.019)*** | (0.047) | (0.004)*** | (0.005)*** | (0.017)*** | (0.008) | (0.008) | (0.028)*** |
| Quintile 4 | -0.035 | -0.046 | -0.188 | -0.016 | 0.008 | -0.037 | 0.004 | 0.011 | -0.109 |
| | (0.010)*** | (0.018)** | (0.036)*** | (0.004)*** | (0.004)* | (0.018)** | (0.008) | (0.009) | (0.023)*** |
| Constant | -0.111 | 0.029 | 0.136 | -0.311 | -0.230 | -0.063 | -0.264 | -0.187 | 0.031 |
| | (0.008)*** | (0.017)* | (0.029)*** | (0.004)*** | (0.003)*** | (0.013)*** | (0.006)*** | (0.007)*** | (0.020) |
| Obs. | 591 | 349 | 256 | 1244 | 931 | 616 | 1835 | 1280 | 872 |

**Note:** All differences measured relative to quintile 5, the reference category. Robust standard errors in parenthesis. * significant at 10%; ** significant at 5%; *** significant at 1%.

**TABLE 5 – Differences in conditional returns to Ethnicity,** relative to the formal sector: by unconditional *per capita* household income quintile.

| | Informal Salaried | | | Self Employed | | | Informal Sector | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1993 | 1997 | 2002 | 1993 | 1997 | 2002 | 1993 | 1997 | 2002 |
| Quintile 1 | 0.003 | 0.054 | 0.114 | 0.030 | -0.070 | 0.035 | 0.014 | -0.045 | 0.055 |
| | (0.009) | (0.016)*** | (0.032)*** | (0.005)*** | (0.009)*** | (0.021)* | (0.006)** | (0.009)*** | (0.017)*** |
| Quintile 2 | -0.007 | 0.036 | 0.070 | 0.015 | -0.067 | 0.018 | 0.011 | -0.036 | 0.042 |
| | (0.008) | (0.014)*** | (0.026)*** | (0.005)*** | (0.009)*** | (0.020) | (0.006)* | (0.009)*** | (0.016)*** |
| Quintile 3 | -0.017 | 0.028 | 0.058 | -0.002 | -0.048 | -0.023 | -0.003 | -0.034 | 0.005 |
| | (0.008)** | (0.014)* | (0.030)* | (0.005) | (0.009)*** | (0.019) | (0.006) | (0.009)*** | (0.016) |
| Quintile 4 | -0.012 | 0.005 | 0.079 | 0.006 | -0.029 | -0.002 | 0.008 | -0.020 | 0.028 |
| | (0.008) | (0.012) | (0.031)** | (0.005) | (0.009)*** | (0.019) | (0.006) | (0.009)** | (0.017)* |
| Constant | 0.126 | 0.131 | 0.068 | 0.018 | 0.073 | 0.073 | 0.050 | 0.080 | 0.071 |
| | (0.007)*** | (0.010)*** | (0.018)*** | (0.004)*** | (0.008)*** | (0.016)*** | (0.005)*** | (0.008)*** | (0.012)*** |
| Obs. | 611 | 246 | 241 | 1480 | 887 | 709 | 2091 | 1133 | 950 |

**Note:** All differences measured relative to quintile 5, the reference category. Robust standard errors in parenthesis. * significant at 10%; ** significant at 5%; *** significant at 1%.

**TABLE 6 – Differences in conditional returns to Basic Education,** relative to the formal sector: by unconditional *per capita* household income quintile.

| | Informal Salaried | | | Self Employed | | | Informal Sector | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1993 | 1997 | 2002 | 1993 | 1997 | 2002 | 1993 | 1997 | 2002 |
| Quintile 1 | -0.037 | -0.131 | 0.046 | -0.042 | -0.108 | -0.025 | -0.017 | -0.104 | -0.074 |
| | (0.014)** | (0.061)** | (0.038) | (0.009)*** | (0.018)*** | (0.018) | (0.013) | (0.019)*** | (0.028)*** |
| Quintile 2 | -0.023 | -0.124 | 0.021 | -0.032 | -0.084 | -0.028 | -0.027 | -0.085 | -0.032 |
| | (0.013)* | (0.059)** | (0.024) | (0.009)*** | (0.018)*** | (0.018) | (0.013)** | (0.018)*** | (0.028) |
| Quintile 3 | -0.024 | -0.081 | 0.090 | -0.027 | -0.077 | -0.008 | -0.027 | -0.067 | -0.051 |
| | (0.012)** | (0.059) | (0.031)*** | (0.009)*** | (0.019)*** | (0.016) | (0.013)** | (0.019)*** | (0.029)* |
| Quintile 4 | -0.013 | -0.029 | 0.037 | -0.020 | -0.048 | -0.028 | -0.030 | -0.036 | -0.021 |
| | (0.013) | (0.060) | (0.029) | (0.009)** | (0.018)*** | (0.017) | (0.012)** | (0.019)* | (0.029) |
| Constant | 0.035 | 0.237 | 0.122 | 0.233 | 0.168 | -0.063 | 0.155 | 0.177 | 0.043 |
| | (0.011)*** | (0.055)*** | (0.014)*** | (0.008)*** | (0.015)*** | (0.014)*** | (0.010)*** | (0.016)*** | (0.021)** |
| Obs. | 361 | 155 | 108 | 561 | 372 | 250 | 922 | 527 | 358 |

**Note:** All differences measured relative to quintile 5, the reference category. Robust standard errors in parenthesis. * significant at 10%; ** significant at 5%; *** significant at 1%.

**TABLE 7 – Differences in conditional returns to Primary Education,**
relative to the formal sector: by unconditional *per capita* household income quintile.

| | Informal Salaried | | | Self Employed | | | Informal Sector | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1993 | 1997 | 2002 | 1993 | 1997 | 2002 | 1993 | 1997 | 2002 |
| Quintile 1 | -0.007 | -0.115 | 0.087 | -0.075 | -0.086 | 0.094 | -0.057 | -0.090 | 0.116 |
| | (0.009) | (0.048)** | (0.045)* | (0.013)*** | (0.018)*** | (0.028)*** | (0.015)*** | (0.020)*** | (0.031)*** |
| Quintile 2 | -0.005 | -0.070 | 0.077 | -0.051 | -0.050 | 0.109 | -0.051 | -0.044 | 0.094 |
| | (0.008) | (0.041)* | (0.037)** | (0.012)*** | (0.016)*** | (0.028)*** | (0.014)*** | (0.018)** | (0.030)*** |
| Quintile 3 | 0.001 | -0.038 | 0.048 | -0.052 | -0.015 | 0.032 | -0.041 | -0.016 | 0.039 |
| | (0.009) | (0.038) | (0.031) | (0.012)*** | (0.015) | (0.025) | (0.014)*** | (0.016) | (0.027) |
| Quintile 4 | -0.003 | 0.008 | 0.055 | -0.023 | 0.002 | 0.010 | -0.036 | 0.006 | 0.016 |
| | (0.008) | (0.037) | (0.027)** | (0.013)* | (0.015) | (0.022) | (0.014)** | (0.016) | (0.024) |
| Constant | 0.024 | 0.145 | -0.159 | 0.240 | 0.046 | 0.039 | 0.159 | 0.069 | -0.044 |
| | (0.007)*** | (0.032)*** | (0.019)*** | (0.010)*** | (0.013)*** | (0.016)** | (0.012)*** | (0.013)*** | (0.018)** |
| Obs. | 341 | 194 | 140 | 433 | 431 | 259 | 774 | 625 | 399 |

**Note:** All differences measured relative to quintile 5, the reference category. Robust standard errors in parenthesis. * significant at 10%; ** significant at 5%; *** significant at 1%.

**TABLE 8 – Differences in conditional returns to Secondary Education,**
relative to the formal sector: by unconditional *per capita* household income quintile.

| | Informal Salaried | | | Self Employed | | | Informal Sector | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1993 | 1997 | 2002 | 1993 | 1997 | 2002 | 1993 | 1997 | 2002 |
| Quintile 1 | 0.027 | -0.102 | 0.230 | -0.062 | -0.023 | 0.199 | -0.047 | -0.033 | 0.219 |
| | (0.011)** | (0.047)** | (0.131)* | (0.016)*** | (0.008)*** | (0.070)*** | (0.012)*** | (0.018)* | (0.061)*** |
| Quintile 2 | 0.013 | -0.035 | 0.109 | -0.047 | -0.021 | 0.154 | -0.047 | 0.017 | 0.115 |
| | (0.010) | (0.032) | (0.034)*** | (0.017)*** | (0.007)*** | (0.062)** | (0.012)*** | (0.020) | (0.038)*** |
| Quintile 3 | 0.019 | -0.013 | 0.055 | -0.050 | -0.017 | 0.052 | -0.042 | -0.006 | 0.039 |
| | (0.010)* | (0.028) | (0.023)** | (0.016)*** | (0.006)*** | (0.049) | (0.012)*** | (0.015) | (0.030) |
| Quintile 4 | 0.007 | 0.012 | 0.070 | -0.032 | -0.015 | 0.054 | -0.031 | 0.024 | 0.046 |
| | (0.009) | (0.023) | (0.021)*** | (0.015)** | (0.006)** | (0.047) | (0.012)*** | (0.015) | (0.029) |
| Constant | 0.055 | -0.004 | -0.373 | 0.165 | -0.201 | -0.294 | 0.142 | -0.161 | -0.319 |
| | (0.007)*** | (0.019) | (0.007)*** | (0.011)*** | (0.005)*** | (0.029)*** | (0.009)*** | (0.010)*** | (0.020)*** |
| Obs. | 203 | 176 | 127 | 396 | 373 | 238 | 599 | 549 | 365 |

**Note:** All differences measured relative to quintile 5, the reference category. Robust standard errors in parenthesis. * significant at 10%; ** significant at 5%; *** significant at 1%.

**TABLE 9 – Differences in conditional returns to Technical Education,**
relative to the formal sector: by unconditional *per capita* household income quintile.

| | Informal Salaried | | | Self Employed | | | Informal Sector | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1993 | 1997 | 2002 | 1993 | 1997 | 2002 | 1993 | 1997 | 2002 |
| Quintile 1 | 0.002 | -0.658 | 0.255 | -0.270 | -0.148 | 0.034 | -0.277 | -0.318 | 0.124 |
| | (0.035) | (0.262)** | (0.167) | (0.045)*** | (0.068)** | (0.033) | (0.065)*** | (0.119)*** | (0.164) |
| Quintile 2 | 0.061 | -1.192 | -0.385 | -0.159 | -0.119 | -0.001 | -0.072 | -0.385 | -0.155 |
| | (0.039) | (0.067)*** | (0.190)* | (0.049)*** | (0.036)*** | (0.034) | (0.067) | (0.082)*** | (0.103) |
| Quintile 3 | 0.002 | -0.520 | -0.148 | -0.117 | -0.049 | 0.217 | -0.125 | -0.198 | 0.030 |
| | (0.065) | (0.114)*** | (0.226) | (0.058)** | (0.023)** | (0.086)** | (0.065)* | (0.089)** | (0.127) |
| Quintile 4 | 0.026 | -0.221 | -0.296 | -0.091 | -0.036 | 0.122 | -0.038 | -0.160 | -0.087 |
| | (0.033) | (0.112)* | (0.178) | (0.047)* | (0.018)** | (0.054)** | (0.055) | (0.091)* | (0.106) |
| Constant | 0.217 | 0.446 | -0.493 | -0.131 | -0.498 | -0.731 | -0.057 | -0.235 | -0.612 |
| | (0.023)*** | (0.067)*** | (0.167)*** | (0.034)*** | (0.010)*** | (0.027)*** | (0.035) | (0.074)*** | (0.098)*** |
| Obs. | 44 | 36 | 27 | 115 | 109 | 50 | 159 | 145 | 77 |

**Note:** All differences measured relative to quintile 5, the reference category. Robust standard errors in parenthesis. * significant at 10%; ** significant at 5%; *** significant at 1%.

**TABLE 10 – Differences in conditional returns to University Education,** relative to the formal sector: by unconditional *per capita* household income quintile.

| | Informal Salaried | | | Self Employed | | | Informal Sector | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1993 | 1997 | 2002 | 1993 | 1997 | 2002 | 1993 | 1997 | 2002 |
| Quintile 1 | 0.169 | -0.540 | 0.000 | -0.052 | 0.146 | -0.042 | -0.032 | 0.085 | -0.009 |
| | (0.045)*** | (0.123)*** | (0.000) | (0.015)*** | (0.033)*** | (0.066) | (0.026) | (0.040)** | (0.065) |
| Quintile 2 | 0.171 | -0.289 | 0.020 | -0.052 | 0.127 | -0.148 | -0.050 | 0.094 | -0.119 |
| | (0.109) | (0.087)*** | (0.142) | (0.015)*** | (0.031)*** | (0.040)*** | (0.056) | (0.037)** | (0.086) |
| Quintile 3 | 0.054 | -0.437 | 0.154 | -0.178 | 0.062 | -0.121 | -0.170 | 0.036 | -0.064 |
| | (0.076) | (0.103)*** | (0.256) | (0.046)*** | (0.035)* | (0.055)** | (0.043)*** | (0.038) | (0.063) |
| Quintile 4 | 0.015 | -0.151 | 0.007 | -0.047 | 0.076 | -0.139 | -0.043 | 0.050 | -0.114 |
| | (0.064) | (0.201) | (0.051) | (0.024)* | (0.024)*** | (0.045)*** | (0.029) | (0.036) | (0.037)*** |
| Constant | -0.262 | 0.005 | -0.977 | 0.051 | -0.647 | -0.804 | 0.012 | -0.596 | -0.837 |
| | (0.045)*** | (0.087) | (0.044)*** | (0.015)*** | (0.016)*** | (0.030)*** | (0.017) | (0.023)*** | (0.027)*** |
| Obs. | 28 | 21 | 17 | 114 | 124 | 82 | 142 | 145 | 99 |

**Note:** All differences measured relative to quintile 5, the reference category. Robust standard errors in parenthesis. * significant at 10%; ** significant at 5%; *** significant at 1%.

**FIGURE 1A- Density of log hourly earnings by sector, metropolitan areas. (Bs$, 2002)**

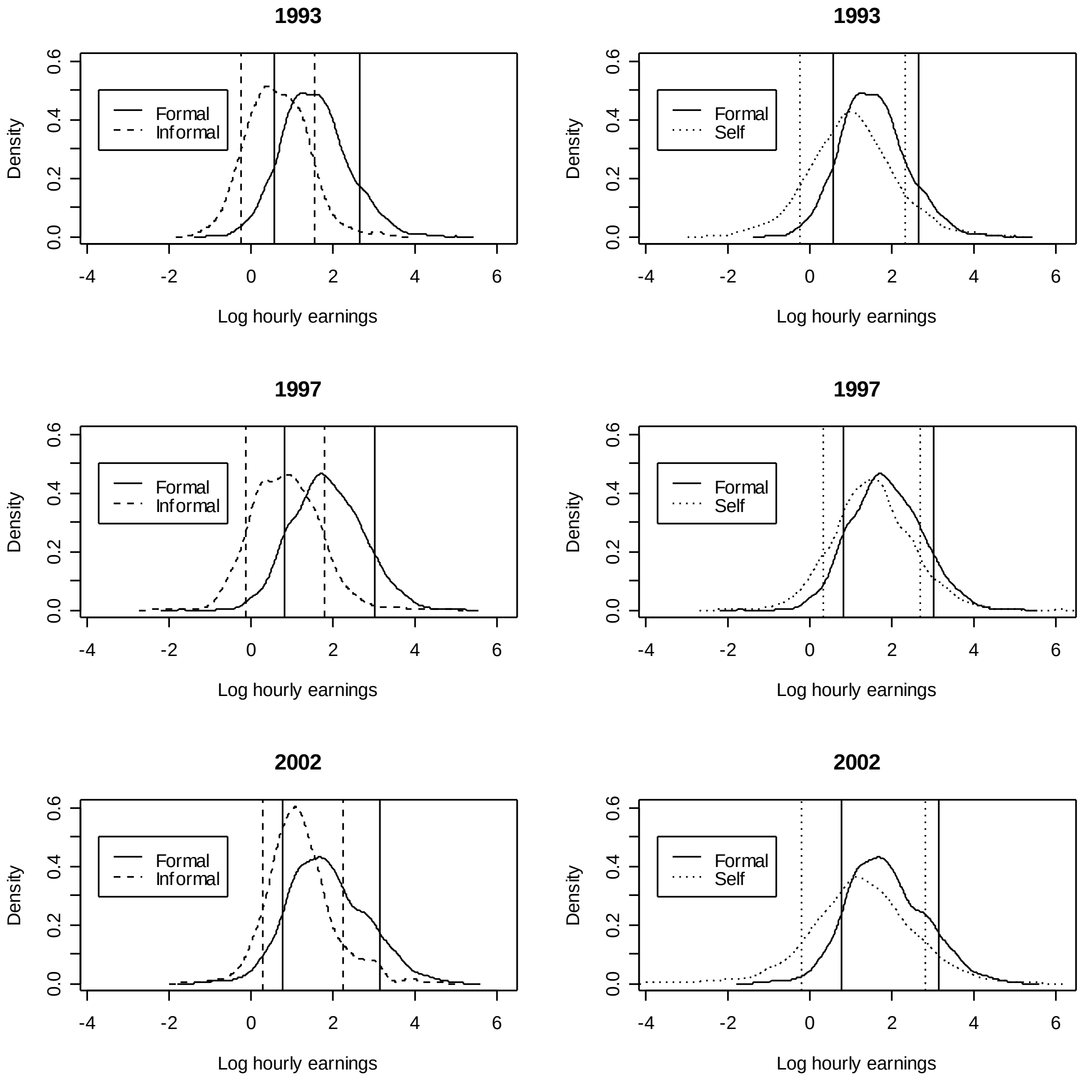


**FIGURE 1B- Quantile Wage Functions**

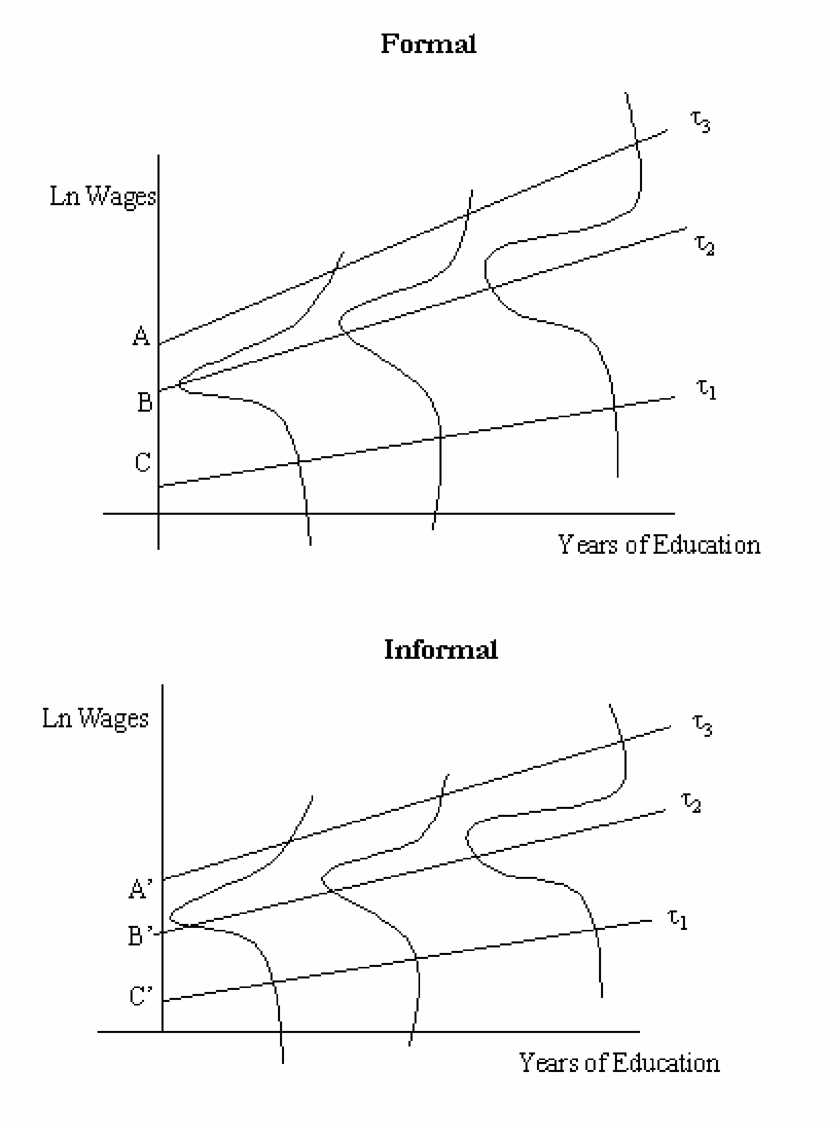


**FIGURE 2A - Formal Sector Coefficients, 2002 (10% confidence intervals)**

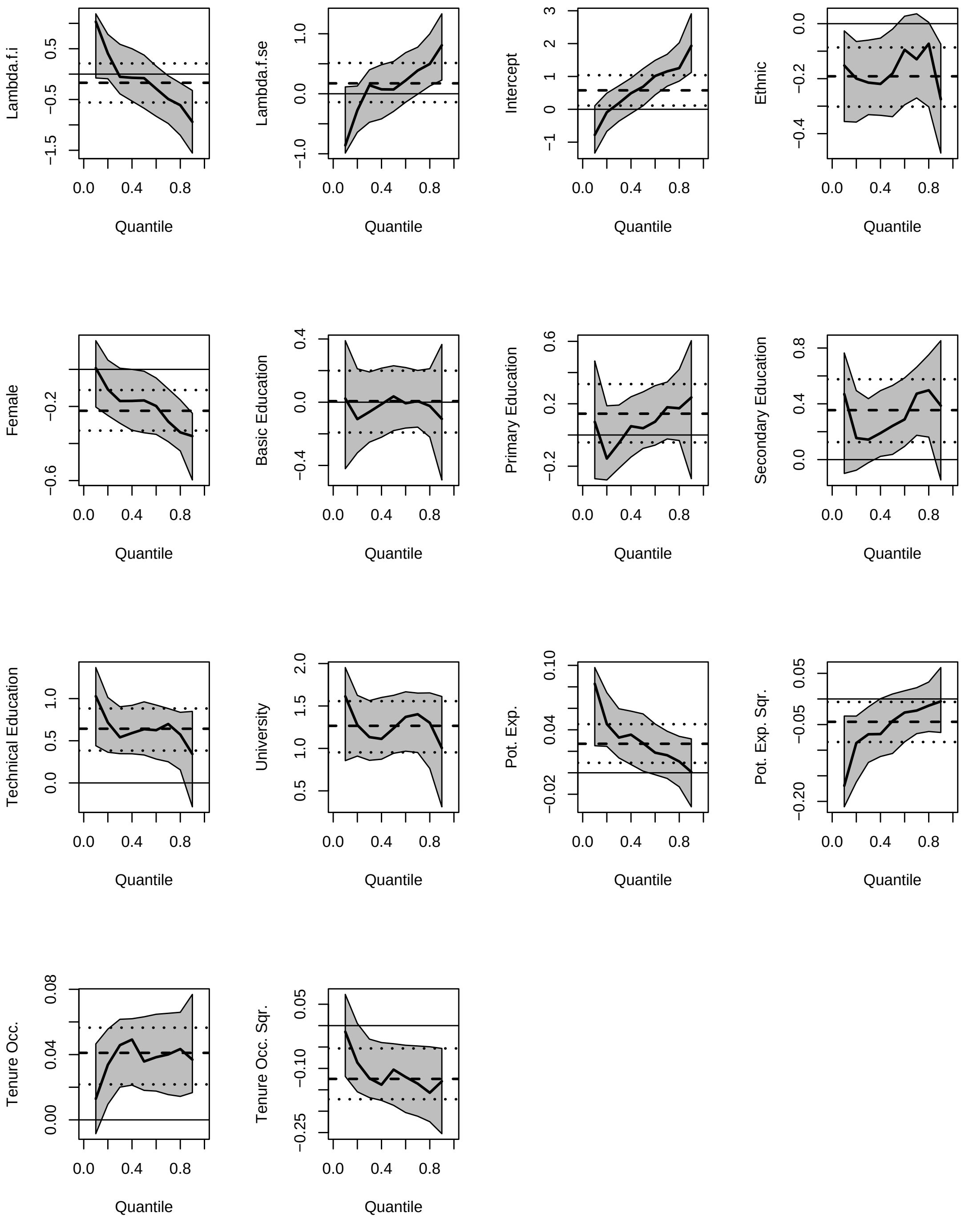


**FIGURE 2B - 1997 Formal Sector Coefficients (10% confidence intervals)**

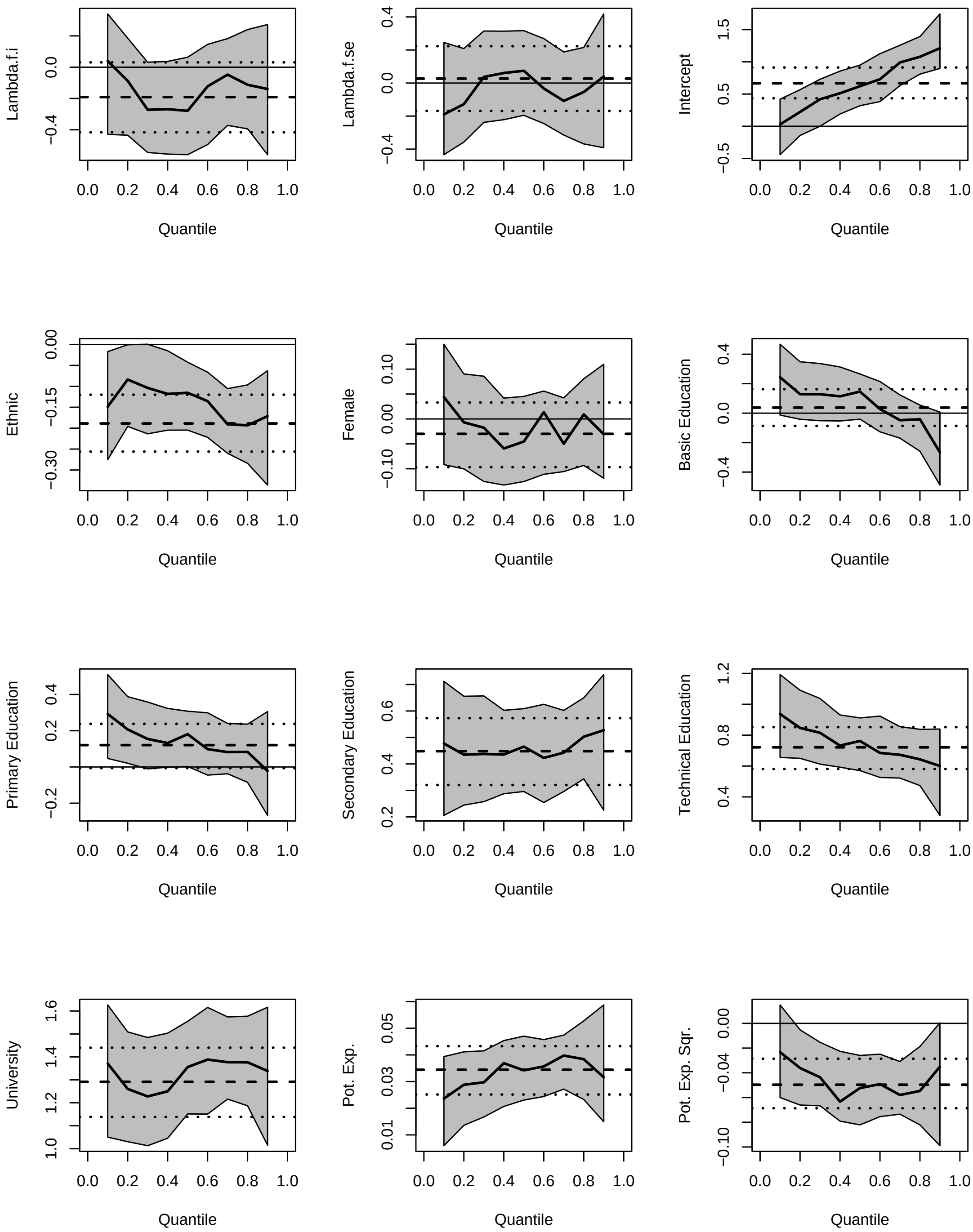


**FIGURE 2C - 1993 Formal Sector Coefficients (10% confidence intervals)**

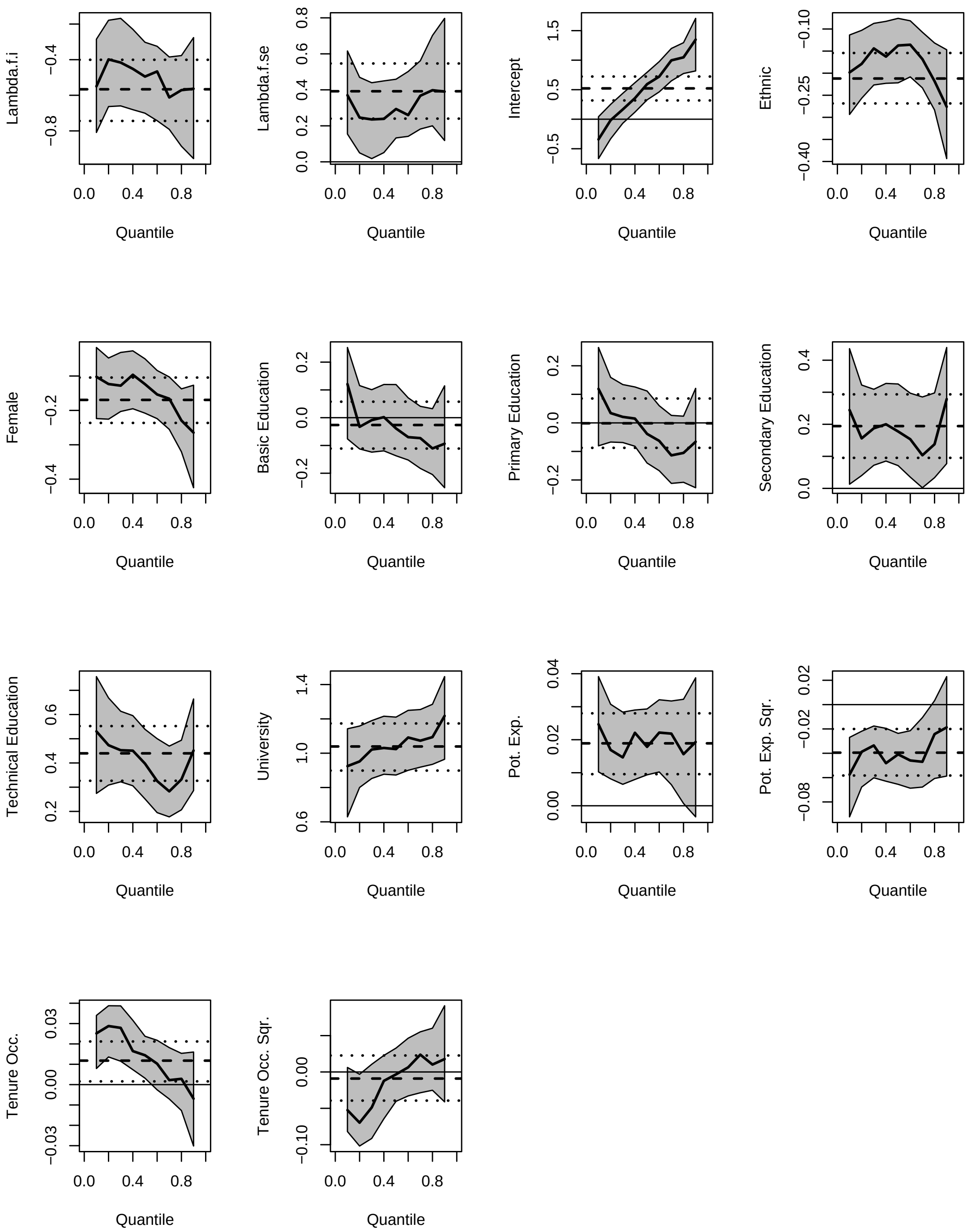
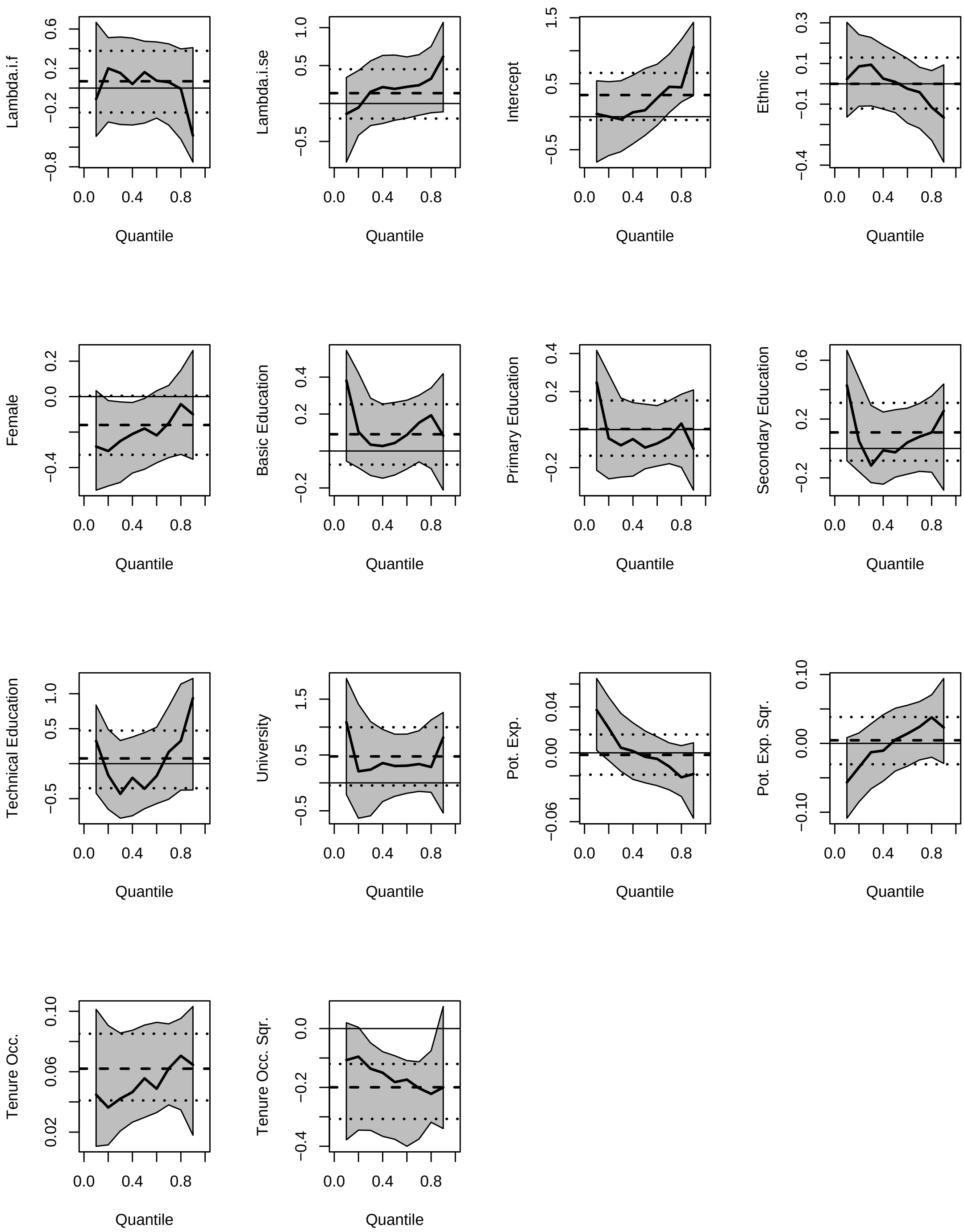
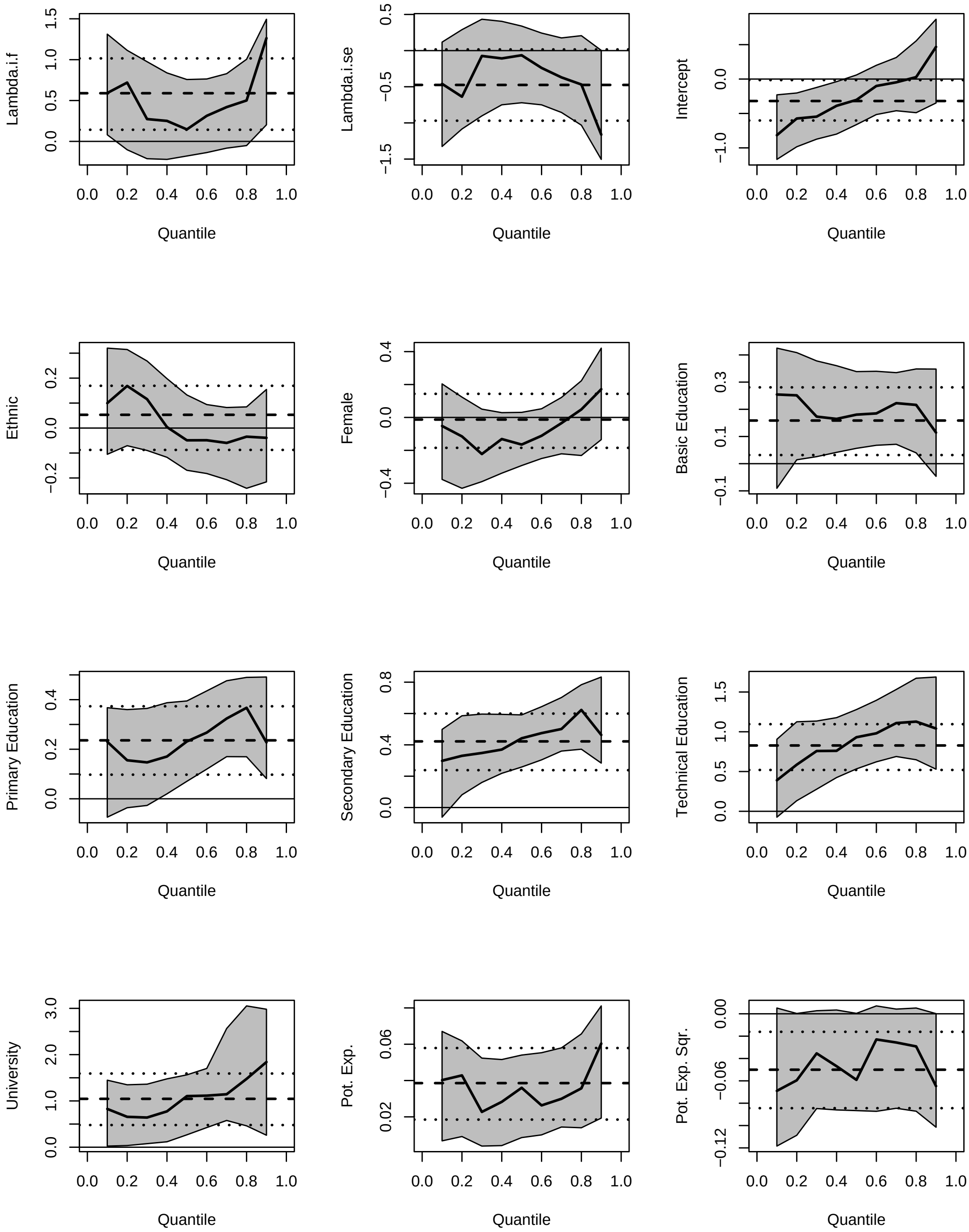


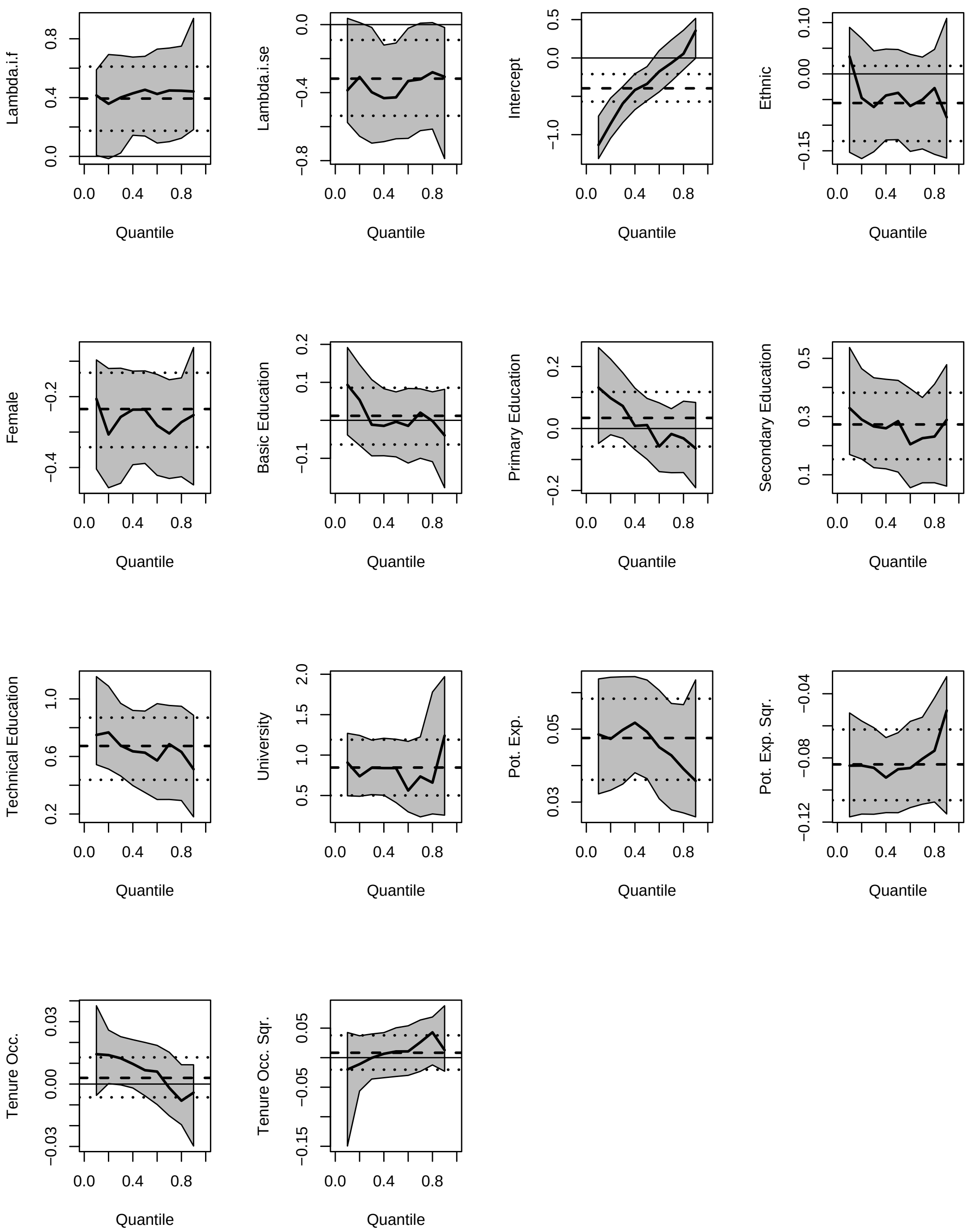
**FIGURE 3A - 2002 Informal Sector Coefficients (10% Confidence intervals)**



## FIGURE 3B - 1997 Informal Sector Coefficients (10% Confidence intervals)



## FIGURE 3C - 1993 Informal Sector Coefficients (10% Confidence intervals)



## FIGURE 4A - 2002 Self-employed Coefficients (10% Confidence intervals)

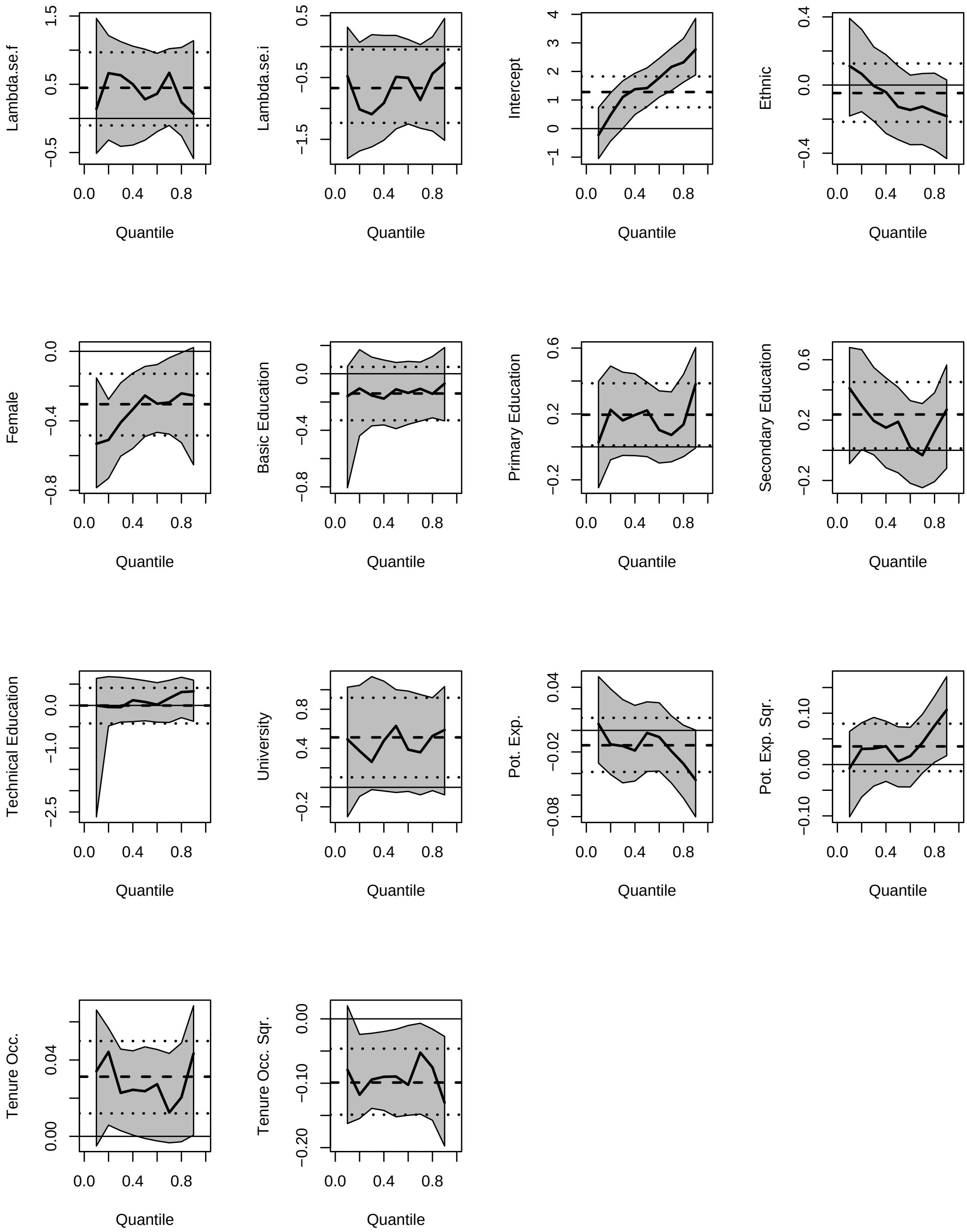


**FIGURE 4B - 1997 Self-employed Coefficients (10% Confidence intervals)**

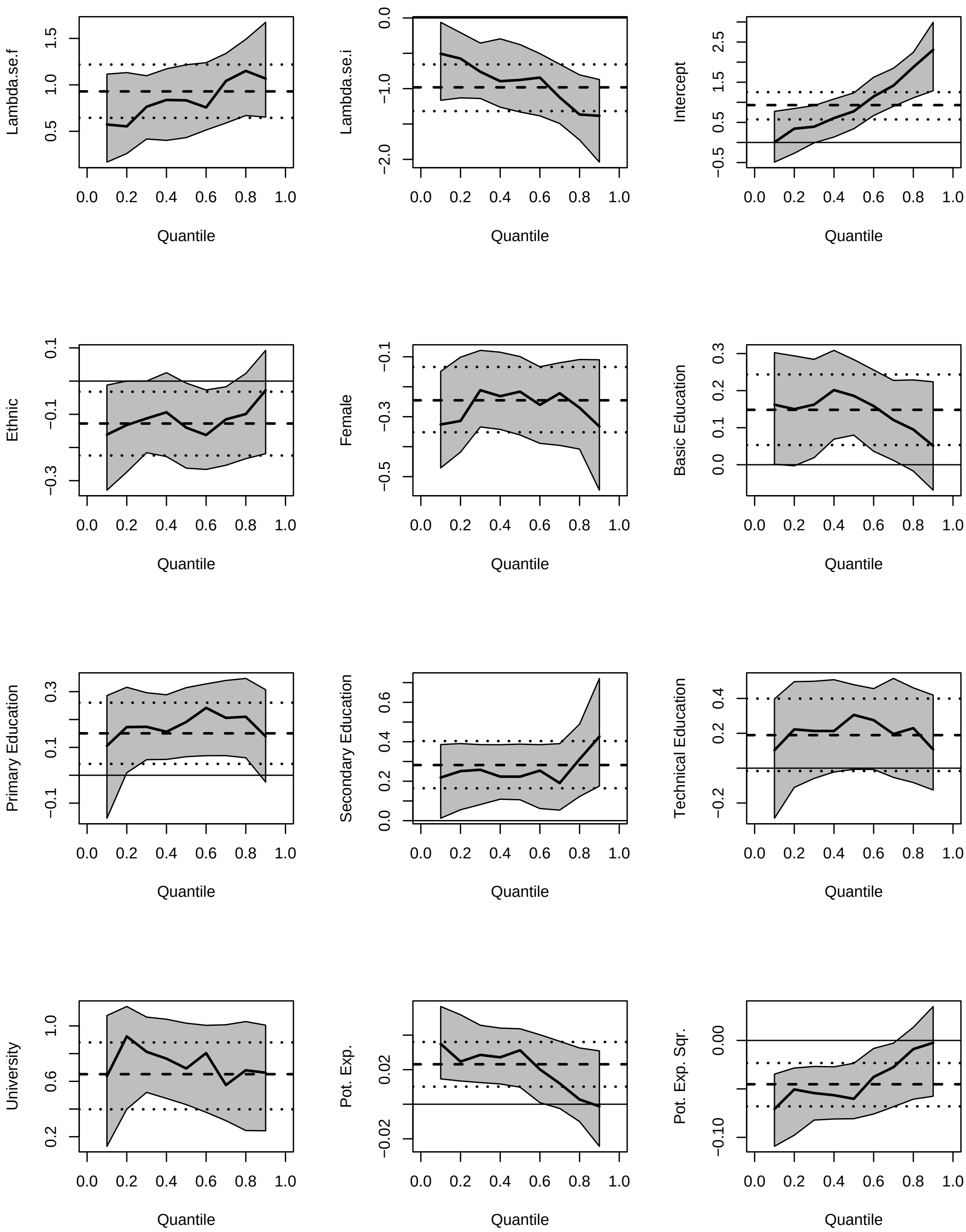


**FIGURE 4C - 1993 Self-employed Coefficients (10% Confidence intervals)**