

Wage Inequality and Return to Education in Chile, 1974–2007^{*}

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Abstract

This study analyzes the validity of using return to higher education, an education-based measure of skill premium, as a measure of wage inequality, when taking sample selection bias into consideration; it uses data drawn from Chile's trade liberalization period. The findings show that the return to higher education estimated by both ordinary least squares (OLS) and Heckman two-step procedures (Heckit), as well as other measures of wage inequality such as the Gini of wages, tended to move precisely in the same direction up to the early 1990s; this was true, especially in the aftermath of trade liberalization, in spite of persistent highly fluctuations in the unemployment rate during the mid-1970s and the 1980s. However, the return to higher education estimated by Heckit is substantially larger than that by OLS in more recent, post-2002 periods, although OLS and Heckit estimates of return to higher education still tended to move in a similar direction in this period. Therefore, we find that the use of the return to higher education as estimated by OLS, while limiting the sample to full-time salaried male workers, as a measure of wage inequality should not be overly problematic, although we need to be more cautious about the presence of selection bias in more recent periods.

JEL classification: J31, O15

Key words: Chile, Skill premium, Return to education, Sample selection bias

1. Introduction

Chile is the first of Latin American and Caribbean countries (henceforth, LACs) to convert from import substitution industrialization (henceforth ISI) to far-reaching trade liberalization, following the military *coup d'état* that overthrew Allende's government in 1973. Thus, among LACs, Chile has the longest history of external reforms. Moreover, the external reform-experiences in Chile are not

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uniform, but have at least three sub-periods (Ffrench-Davis, 2005; 2010). In this regard, Chile represents unique example not only because of the long history of economic liberalization but also because the country had reacted to global economic change by applying pragmatic modifications to the original pure neo-liberal reforms, which might have had relevant distributional impacts. Therefore, the analysis of changes in wage inequality in Chile has been very interesting for other LACs that liberalized their trade regimes later in the 1980s and 1990s and had implemented the first stage of external reforms (i.e., import liberalization) or where the second or third stage of external reforms (i.e., export promotion or reciprocal trade liberalization) have just begun; through such analysis, we can see whether different periods of external reforms produced different trends of inequality in Chile.

In this regard, this study engages in a detailed analysis of changes in wage inequality in Chile after the post-1974 trade liberalization period, by using the narrowest measure of inequality—namely, skill premium, or returns to skill—as a measure of wage inequality. Goldberg and Pavcnik (2007) point out that this narrowest measure of inequality has been used widely in the literature on globalization and inequality, because the increase in inequality documented in many developing countries has been associated with an increase in skill premiums. Moreover, they mention that in several countries, changes in skill premiums seem to chronologically coincide with trade reforms. In that sense, skill premiums constitute a very suitable measure of inequality if we focus on an analysis on wage-inequality change following trade liberalization. In addition to the advantages this measure bears as an indicator, when information on an individual's education attainment is available, we can easily use return to higher education as a measure of skill premium (Goldberg and Pavcnik, 2007).

However, we need to be cautious when using return to higher education as a measure of wage inequality; this is because, as a considerable volume of labor economics literature points out, estimates of return to education are biased in the presence of violations of OLS assumptions, such as measurement error, endogeneity, and sample selection bias. In the case of Chile, endogeneity problems caused by omitted and unobservable individual-level characteristics, Contreras *et al.* (1999) show that the extent of overestimation of the rate of an additional year of education is approximately only 1%, by using the education attainments of parents as a proxy of unobservable individual characteristics. On the other hand, most previous studies that analyze return to education in Chile—such as Montenegro (1998), Mideplan (2000) and Contreras (2002)—limit the sample to full-time salaried male workers. Thus, they yield biased estimates as long as the decision to be a full-time labor force participant does not affect the determinants of wage.

If we review the process by which external reforms occurred in Chile, it chronologically coincides with the many other reforms (e.g., stabilization programs, macroeconomic adjustments,

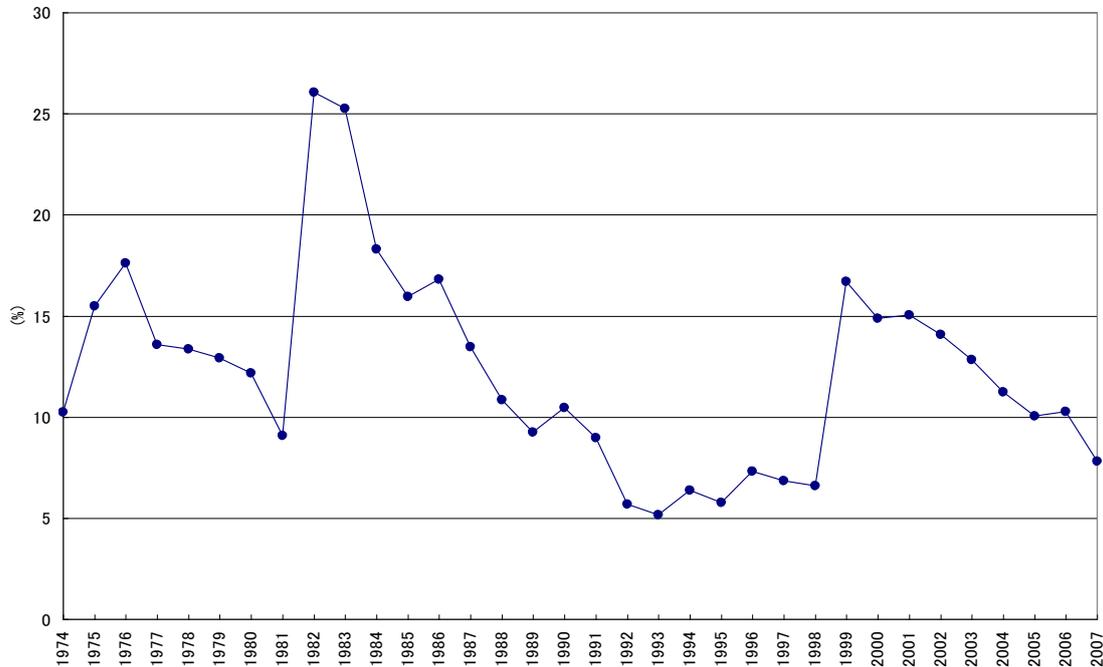
wide-ranging privatization, financial sector reforms, tax reforms, and labor market reforms). Those reforms incurred huge adjustment costs, such as persistently high unemployment, squeeze on real minimum wages, especially in the first and second subperiods of the external reforms.¹ As discussed in greater detail in section 3-2, the smaller the probability of labor-force participation—that is, the higher the unemployment rate is, the larger sample selection bias will become. Moreover, the unemployment rate fluctuated greatly during the period under analysis; it sometimes jumped after an economic crisis (e.g., between 1974 and 1976; after the shock stabilization program, between 1981 and 1982; after the debt crisis, between 1998 and 1999; and after the contagion of the Asian financial crisis [see Figure 1]). Therefore, we must assume that the impact of sample selection bias cannot be ignored during 1974–2007 in Chile, especially in the period during which the unemployment rate fluctuated greatly.

Therefore, the objective of this study is to analyze the validity of return to higher education as a measure of wage inequality, when taking sample selection bias into consideration and by using data from the trade liberalization period in Chile. If we find that the changes in the return to higher education as estimated by OLS, while limiting the sample to full-time male workers, the return to higher education as estimated by Heckman selection bias correction procedures—as well as other measures of wage inequality, such as the Gini of wages—tend to move in the same direction, we can confirm the validity of the return to higher education as a measure of wage inequality in the presence of sample selection bias.

This paper is organized as follows. Section 2 describes the data used herein and presents descriptive statistics concerning the changes in wage inequality, education attainment and the industrial sector's share in the total employment. Section 3 details the specifications of wage equation, as well as the estimation method for Heckman selection bias correction procedures. Section 4 presents the findings of econometric analysis, while Section 5 provides concluding remarks.

¹ The real indices of minimum wage in 1989 (1989=100) were squeezed to levels lower than those in 1970 (108.9), but they have drastically increased since 1990 becoming 220.3 in 2007 (Ffrench-Davis, 2010: 181).

Figure 1. Changes in the unemployment rate of males in Greater Santiago, 1974–2007 (%)



Source: Author’s calculations based on data from *Encuesta de Ocupación y desocupación en el Gran Santiago*.

2. Data and Descriptive Statistics

This study uses data from the Employment and Unemployment Survey for Greater Santiago (*Encuesta de Ocupación y desocupación en el Gran Santiago*), conducted by the University of Chile. This survey, conducted in June every year, covers the Greater Santiago area, which comprises roughly 40% of Chile’s total population, and is conducted in June every year. Each survey covers a fixed 3600 households² and approximately 10,000 and 14,000 individuals during 1974–2007. The data are repeated cross-section, and the sample is fully representative of the Greater Santiago area.

First, changes in two frequently used wage inequality indicators—that is, the Gini of wages and the variance of the log hourly wages of full-time salaried male workers—are presented in Figure 2. I define “wages” as income from paid employment; thus, wages do not include income from self-employment, assets, pensions, or other sources. The sample used in this study comprises the individuals of working age (14–65 years) who report positive income and a positive number of

² Although the number of households fluctuated during 1957–1979, the number has stayed fixed since 1980.

work hours. Like previous studies, the sample includes only salaried workers—that is, white-collar workers (*empleados*), blue-collar workers (*obreros*), and domestic servants who work on a full-time basis (i.e., more than 30 hours per week).³ Therefore, self-employed—that is, employers and independent workers—are not included. Unpaid family workers and military personnel are also excluded from the sample because their wages are not likely to be determined by market forces. The samples whose variables are not answered or missing in at least one survey question are also eliminated in advance.⁴ Females are also eliminated from the sample, because it is natural to assume that labor market of females are segmented from that of males.⁵

The data trends can be summarized as follows, with the two aforementioned indicators showing very similar trends. Both increased significantly in the aftermath of trade liberalization—that is, the import liberalization period—and reached its peak in 1987, amidst the “pragmatic neo-liberalism with a regressive bias” (Ffrench-Davis, 2005; 2010) period. On the other hand, they substantially decreased during the early 1990s, when “reforms to the neoliberal reforms” (Ffrench-Davis, 2005; 2010) were carried out, although, they temporarily increased in the mid or late-1990s and mid-2000s.⁶ However, they still have not reached the levels of wage inequality seen at the beginning of trade liberalization. Therefore, the findings show that different periods of external reforms certainly produced different trends vis-à-vis wage inequality in Chile. Moreover, changes in the aforementioned wage-based measures of inequality indicate trends very similar those of income-based measures of inequality (cf. Larrañaga, 2001); the Gini of incomes increased significantly since the mid-1970s, reached its peak in 1987, then decreased substantially in the early 1990s. Therefore, the findings show that limiting the components of income to wages and the sample to full-time salaried male workers would not lead to bias in measurements of inequality, although the absolute levels of the Gini coefficients in themselves are stably undermeasured during the full period under analysis.

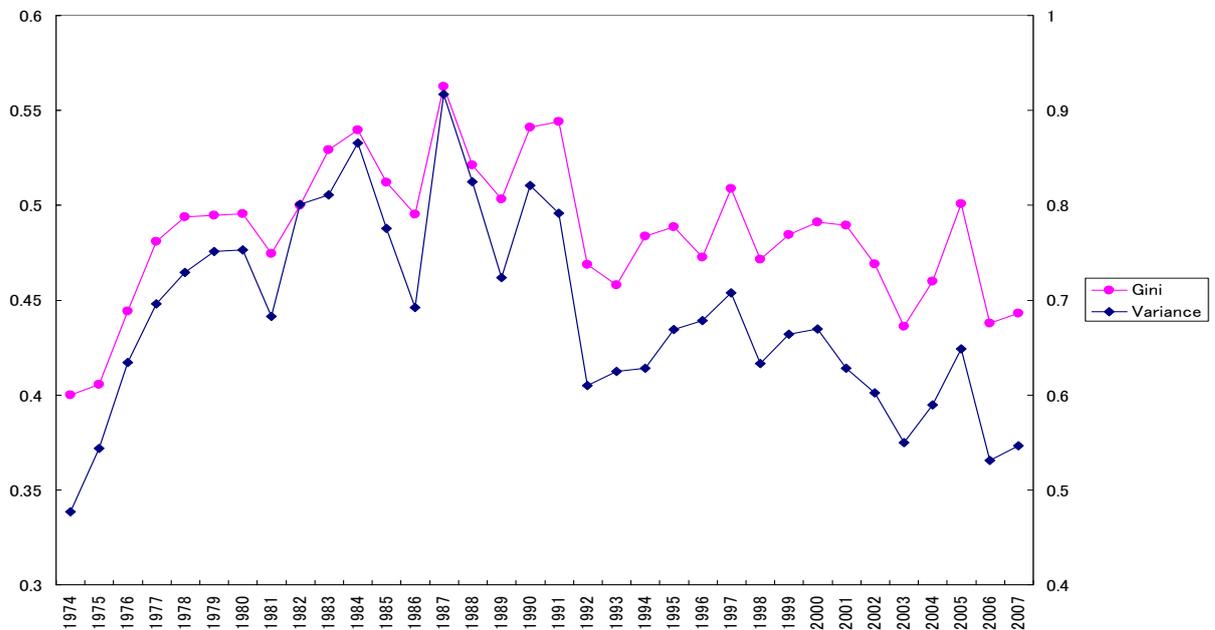
³ Almost all domestic servants are female; thus, they are *de facto* excluded when limiting the sample to male workers.

⁴ I also exclude the samples whose pre-1997 education attainments are “special schools.” Although some “special schools” seem to be secondary schools—especially in the 1990s—they constitute an ambiguous and inconsistent category during the entire analysis period.

⁵ However, I find that the return to an additional year of education has not been statistically different between males and females in the recent years.

⁶ The worsening of wage inequality between 1996 and 1999 can be attributable to the contagion of external negative shocks derived from the Asian financial crisis (Ffrench-Davis, 2010).

Figure 2. Changes in the Gini of wages and the variance of the log hourly wages: full-time salaried male workers in Greater Santiago, 1974–2007



Source: Author’s calculations based on data from *Encuesta de Ocupación y desocupación en el Gran Santiago*.

Second, changes in education attainments within the aforementioned samples are presented in Figure 3. The figure shows stable improvements in education attainment during 1974–2007. The share of workers who had completed only up to primary school education decreased from 63.8% in 1974 to 16.6% in 2007, while the share of workers who had attended up to secondary and higher education was an increasing trend.⁷ However, changes in secondary and higher school education showed another characteristic: the share of workers who had attended up to secondary school education substantially increased until the mid-1980s and after that time, the share remained relatively stable (about 50%); meanwhile, the share of workers who had attended up to higher education increased mainly after the mid-1980s.

⁷ The secondary and higher education categories include both dropouts and graduates. Higher education not only includes university education but also *Centro de Formación Técnica* (CFT)- or *Instituto Profesional* (IP)-based education, which was established by the 1980 higher education reforms in Chile.

Figure 3. Changes in education attainment: full- time salaried male workers in Greater Santiago, 1974–2007



Source: Author’s calculations based on data from *Encuesta de Ocupación y desocupación en el Gran Santiago*.

Finally, the descriptive statistics of full-time salaried male workers in the selected years are presented in Table 1. We can again confirm stable improvements in education attainments with the number of years of schooling increasing from 7.68 in 1974 to 12.00 in 2007. Changes in the industrial sector’s share of total employment are also presented, to show the transformation of employment structure after trade liberalization. The original classification typology features 9 sectors, i.e., agriculture, mining, manufacturing, construction, commerce, financial services, personal services, community services, and transportation. I also break out the manufacturing sector into natural resource-based manufacturing (henceforth, NRBM) and the non-resource-based manufacturing sector.⁸ An especially striking finding in this table is that the employment share of the manufacturing sector—especially that of non-resource-based manufacturing—substantially decreased: 38.0% of full- time salaried male workers were employed in the manufacturing sector at the beginning of trade liberalization, but the ratio persistently decreased, in a trend that became more evident after the 1990s; less than 20% (i.e., 17.3%) of workers were employed by the manufacturing

⁸ I classify the manufacture of foods, beverages, and tobacco; the manufacture of wood and wood products; and the manufacture of paper and paper products as part of NRBM sector.

sector in 2007. Even the employment share of the NRBM sector had been stable or slightly decreased in the Greater Santiago area. On the other hand, the employment share of service sectors—such as commerce and financial service sectors—was persistently increasing. Those situations reflect the de-industrialization of Chile, following trade liberalization.⁹

Table 1. Descriptive statistics of full-time salaried male workers in Greater Santiago, 1974–2007

	1974	1982	1987	1993	1997	2003	2007
Variable Average							
Age	34.32 (12.14)	34.72 (11.45)	34.85 (11.52)	36.48 (11.82)	36.60 (11.48)	37.72 (11.53)	37.86 (12.20)
Years Schooling	7.68 (4.13)	9.28 (4.11)	10.31 (4.05)	10.94 (3.95)	11.07 (4.00)	11.56 (3.60)	12.00 (3.42)
Years of Experience	20.64 (13.03)	19.44 (12.62)	18.54 (12.64)	19.55 (12.88)	19.53 (12.55)	20.16 (12.58)	19.86 (13.21)
Public Sector	0.230 (0.421)	0.125 (0.331)	0.138 (0.345)	0.079 (0.269)	0.070 (0.255)	0.068 (0.252)	0.065 (0.247)
Industrial Sector's Share of Total Employment							
Agriculture	0.021 (0.144)	0.012 (0.109)	0.012 (0.108)	0.011 (0.104)	0.008 (0.090)	0.013 (0.113)	0.009 (0.095)
Mining	0.011 (0.102)	0.006 (0.075)	0.012 (0.110)	0.004 (0.063)	0.006 (0.079)	0.007 (0.086)	0.009 (0.092)
Manufacturing	0.380 (0.485)	0.292 (0.455)	0.295 (0.456)	0.324 (0.468)	0.268 (0.443)	0.236 (0.425)	0.173 (0.379)
NRBM	0.121 (0.326)	0.114 (0.318)	0.121 (0.327)	0.118 (0.323)	0.098 (0.298)	0.102 (0.302)	0.075 (0.263)
Non-resource based manufacturing	0.258 (0.438)	0.178 (0.382)	0.174 (0.379)	0.206 (0.405)	0.170 (0.376)	0.134 (0.341)	0.098 (0.298)
Construction	0.160 (0.367)	0.185 (0.389)	0.129 (0.336)	0.152 (0.359)	0.183 (0.387)	0.137 (0.344)	0.176 (0.381)
Commerce	0.099 (0.299)	0.166 (0.373)	0.157 (0.364)	0.145 (0.352)	0.154 (0.361)	0.174 (0.379)	0.195 (0.397)
Financial services	0.071 (0.258)	0.100 (0.301)	0.111 (0.314)	0.104 (0.305)	0.120 (0.325)	0.147 (0.354)	0.139 (0.346)
Personal services	0.063 (0.243)	0.049 (0.217)	0.062 (0.241)	0.046 (0.209)	0.046 (0.209)	0.047 (0.211)	0.051 (0.221)
Community services	0.088 (0.284)	0.090 (0.287)	0.112 (0.315)	0.104 (0.305)	0.111 (0.314)	0.105 (0.307)	0.111 (0.315)
Transport	0.107 (0.309)	0.098 (0.298)	0.110 (0.313)	0.111 (0.314)	0.105 (0.306)	0.134 (0.341)	0.136 (0.343)
Number of Obs.	1793	1923	1788	1742	1598	2005	1986

Note: Numbers in parentheses are standard deviations.

Source: Author's calculations based on data from *Encuesta de Ocupación y desocupación en el Gran Santiago*.

3. Estimation Method

3-1. Specifications of Wage Equation

We usually estimate return to education based on the Mincerian wage equation, as follows:

$$(1) \quad \ln w_i = \text{cons} + \beta_1 \text{school}_i + \beta_2 \text{exp}_i + \beta_3 \text{exp}_i^2 + X_i' \beta + e_i,$$

⁹ Chile has succeeded in expanding of non-traditional natural resource-based export sectors since the mid-1980s, while the ISI sectors have been pretty much destroyed. However, this employment survey covers only the Greater Santiago area—an urban area that is a part of a metropolitan region; thus, only about 1% of all the workers surveyed there were employed in the agriculture, forestry, or fishing sectors, as shown Table 1. Therefore, this employment survey does not represent the employment structure of the whole of Chile, especially with respect to natural resource related ones.

where w is hourly wage, $school$ is completed years of schooling, exp is years of potential experience in the labor market ($age - school - 6$), and vector X is the observable worker characteristics. β_1 shows the change in wage given a one-unit increase in the number of education years; thus, it can be interpreted as the rate of return to an additional year of education. However, under this specification, the rate of return to an additional year of education is constant across all education attainments. Therefore, I use a spline function, which allows the return to educations to differ among education attainments. This specification is similar to that seen in Contreras *et al.* (1999).

(2)

$$\ln w_i = cons + \beta_1 school_i + \beta_2 exp_i + \beta_3 exp_i^2 + \beta_4 * d8 * (school - 8) + \beta_5 * d12 * (school - 12) + X_i' \beta + e_i$$

where the dummy variable $d8$ is equal to 1 if an individual has more than 8 completed years of schooling, otherwise; equal to 0. The dummy variable $d12$ is equal to 1 if an individual has more than 12 completed years of schooling, otherwise; equal to 0.¹⁰ In the current study, vector X contains a head of the household dummy, which takes a value of 1 for workers with a position, and 0 otherwise; public sector dummy, which takes a value of 1 for workers employed in the public sector, and 0 otherwise; and 9 industry indicators, which are detailed in the previous section.¹¹ In this specification, β_1 , $\beta_1 + \beta_4$, and $\beta_1 + \beta_4 + \beta_5$ show the return to primary, secondary, and higher education, respectively. Previous studies, such as those of Mideplan (2000) and Contreras (2002), estimate equation (2) by OLS.

3-2. The Estimation Method for the Heckman Model

As mentioned in the introduction, the estimates will be biased as long as full-time labor force participation does not affect the determinants of wage. In this regard, the Heckman selection correction procedure might be useful. To simplify the notation, I rewrite as x the set of containing all the independent variables of the wage equation (2). z is also a set of independent variables of

¹⁰ Chile's school system had an 8-4 structure after 1965 and a 6-6 structure before that year. This employment survey converts the years of schooling from the older system into those of the current system. For example, an individual who received up to the second year of schooling in the older system of secondary school is treated as having 8 years of schooling.

¹¹ The industry indicators are classified as follows: agriculture, mining, NRBM, nonresource-based manufacturing, construction, commerce, financial services, personal services, community services, and transportation. Construction is chosen as a base category because it holds a relatively large employment share among non-trade sectors; its share is stable for the whole of the analysis period, as seen in Table 1.

participation equation, and it determines whether or not an individual i is a full-time wage worker.

$$(3) \quad \ln w_i^* = x_i' \beta_0 + e_i$$

$$w_i = w_i^* \quad \text{if } z_i' \gamma_0 + u_i > 0 \Leftrightarrow d_i = 1$$

$$= 0 \quad \text{if } z_i' \gamma_0 + u_i \leq 0 \Leftrightarrow d_i = 0,$$

where w_i^* shows individual i 's latent offered wage including unobserved samples. d_i is a dummy variable that takes a value of 1 or 0 when individual i is a full-time salaried worker or not, respectively. Thus, individual i 's wage becomes observable—that is, he decides to be in the sample of workers ($d_i = 1$) only when his offered wage exceeds his reservation wage ($z_i' \gamma_0 + u_i > 0$). We assume that e_i and u_i have a bivariate normal distribution with zero means, a known covariance matrix and correlation coefficient ρ :¹²

$$(4) \quad \begin{pmatrix} e_i \\ u_i \end{pmatrix} \sim N \left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_e^2 & \rho \sigma_e \sigma_u \\ \rho \sigma_u \sigma_e & \sigma_u^2 \end{pmatrix} \right).$$

Therefore, nonsalaried workers (including part-time workers and unpaid workers)—that is, those outside the sample of the wage equation—consist of those not at all employed. Thus, working-age (14–65 years) unemployed male, male part-time workers, and male unpaid workers are now included in the sample for the participation equation. However, self-employed workers—i.e., employers and independent workers—remain eliminated from the participation equation,¹³ because it is very difficult to find a variable that determines whether an individual is a salaried worker or self-employed. In this regard, it is very feasible to argue that an individual will make the sequential decision to work or not work (including part-time work and unpaid work), and given the decision to work whether as a salaried or self-employed workers (Schafgans, 2000). Alternatively, we can assume that the decision of the individual is to be a salaried worker, self-employed, or not to be

¹² We normally assume $\rho > 0$, because a greater likelihood of labor force participation will be associated with higher wages (Milanovic, 2006). We can relax strong assumptions vis-à-vis the distribution of error terms by applying a semiparametric estimation technique. See, for example, Schafgans (2000).

¹³ The samples whose variables used in the wage equation and participation equation (3) are not answered or missing in at least one survey question are also eliminated in advance.

employed at all. However, from the view point of this study’s objective of pinpointing a precise estimate of return to education—that is, estimating the relationship between education and wage—it does not seem appropriate to include the self-employed in the same manner as salaried workers. First, the “wages” of self-employed individuals are in question, as they need to be separated precisely from asset income (Montenegro, 1998). Moreover, the “wages” of self-employed are determined by virtue of many other factors in addition to the education they have received (Mideplan, 2000).¹⁴ Therefore, I eliminate self-employment individuals in advance from the participation equation in the sample selection correction model.

For identification, at least one variable needs to be included in z that also does not enter x (Schafgans, 2000; Wooldridge, 2003).¹⁵ As Schafgans (2000) and Milanovic (2006) point out, an individual with large non-employment income tends to reduce his or her labor force participation because he or she will be less likely to work for wages, given the higher opportunity cost of being employed.¹⁶ Like those previous studies, I too use the sum of non-employment income—sum of income from assets, pensions, and income from other sources in each household—as the aforementioned identifying variable.¹⁷ In addition to non-employment income, I add the number of children under the age of 14 years in each household to the identifying variable, because a man heading a household with a large number of children is more likely to be working full-time in order to earn more money.

I estimate equation (3) by the Heckman two- step procedure (henceforth, Heckit). We can obtain the conditional expectation of hourly wages of individuals within the sample, as follow:

$$(5) \quad E(\ln w_i | x_i, z_i, d_i = 1) = x_i' \beta_0 + \rho \frac{\sigma_u}{\sigma_e} \lambda\left(\frac{z_i' \gamma_0}{\sigma_u}\right),$$

¹⁴ What is relevant from this issue, Repetto (2005) points out, is that Chile is not a purely meritocratic country; the existing evidence shows that not only education but also socioeconomic origin plays an important role as determinants of wages. This situation is more likely to apply to self-employed workers, especially rich employers.

¹⁵ If all variables of z are equal to those of x , $\hat{\lambda}_i$ can highly correlated with the variables of x_i ; thus, such multicollinearity can lead to very high standard errors among estimates of $\hat{\beta}_0$ (Wooldridge, 2003).

¹⁶ However, Milanovic (2006) does recognize the endogeneity of non-employment income, because high current non-employment income might have resulted from previous labor force participation and high wages.

¹⁷ For example, in this employment survey, house-rent income and estimated rent from the value of royalties (*regalía*) is a component of income from assets. However, I do not include imputed rent as income from assets, because the imputed rent of each household highly correlates with the wages of its members; thus it is apparently an endogenous variable with regard to wages.

where
$$\lambda\left(\frac{z_i'\gamma_0}{\sigma_u}\right) = \frac{\phi\left(\frac{z_i'\gamma_0}{\sigma_u}\right)}{\Phi\left(\frac{z_i'\gamma_0}{\sigma_u}\right)}$$
—that is, an inverse Mills ratio.

It is clear that we will obtain biased estimates of β_0 if we perform OLS while using only the samples whose wages are observable—that is, those with in the sample for the wage equation. Equation (5) also shows that the larger the correlation is between the error terms of the wage equation and those of the participation equation—or the smaller the probability of full-time labor force participation is—the larger the sample selection bias becomes, because we assume ρ is positive and the inverse Mills ratio $\lambda(\cdot)$ is a monotonic decreasing function of the probability that an observation is selected.

We can obtain a reduced form to estimate from equation (2-5) as follows:

$$(6) \quad \ln w_i | x_i, z_i, d_i = 1 = x_i'\beta_0 + \rho \frac{\sigma_u}{\sigma_e} \lambda\left(\frac{z_i'\gamma_0}{\sigma_u}\right) + v_i.$$

We can assume $E(v_i | x_i, z_i, d_i = 1) = 0$. Thus, we can obtain the unbiased estimates of β_0 from equation (2-6). Therefore, the Heckit estimation method is as follows. First, we estimate $\frac{\hat{\gamma}_0}{\sigma_u}$ through the probit of d_i on z_i , using the entire sample, and compute $\hat{\lambda}_i$. Second, using

sample for the wage equation, we regress w_i on x_i and $\hat{\lambda}_i$; then, we can obtain the estimates of

β_0 and $\rho \frac{\sigma_u}{\sigma_e}$. In the Heckit procedures, estimates of β_0 are unbiased.

Equation (6) shows also that the sample selection bias can be considered omitted variable bias. If we perform OLS using only the samples whose wages are observable—that is, if we drop the

inverse Mills ratio term $\lambda\left(\frac{z_i'\gamma_0}{\sigma_u}\right)$ from equation (6)—the term is included in the error term. If

we assume $\rho > 0$ and number of years of schooling positively correlates with the probability of

full-time labor force participation ($\frac{z_i'\gamma_0}{\sigma_u}$), the number of years of schooling negatively correlates

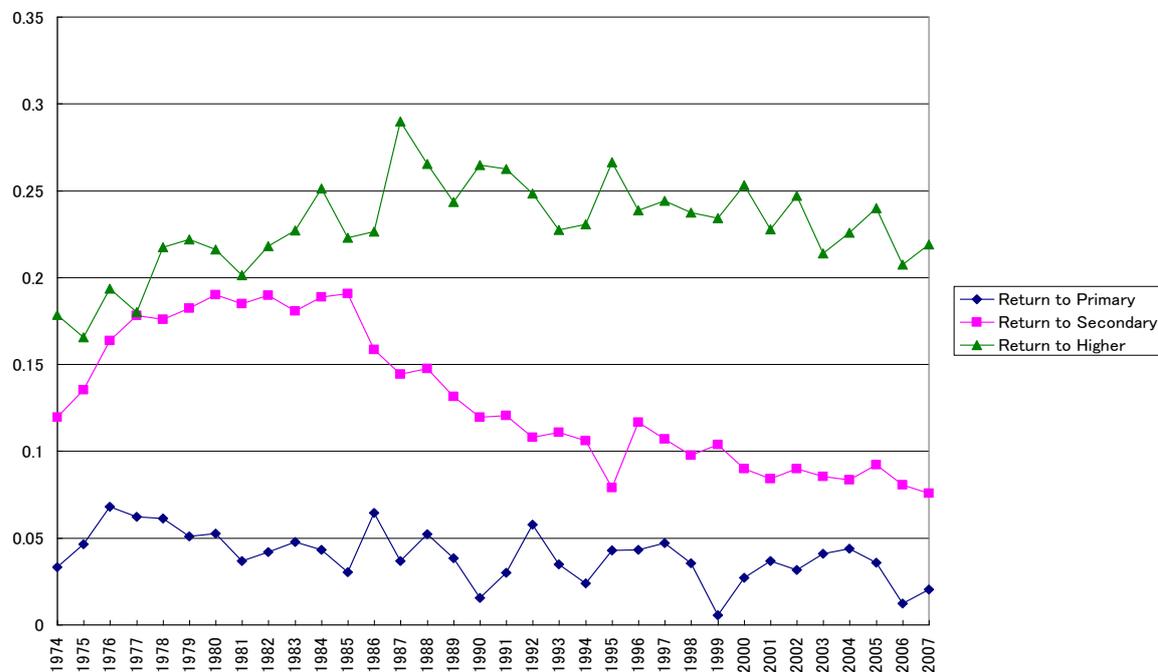
with the omitted variable $\lambda(\frac{z_i'\gamma_0}{\sigma_u})$, because $\lambda(\cdot)$ is a monotonic decreasing function.

Therefore, the omission of the inverse Mills ratio term causes an underestimation of the return to education. This is a highly relevant issue, because “actual” skill premiums as measured by return to education are larger than the frequently used results that limit the sample to full-time salaried male workers.

4. Estimation Results

First, we can see in Figure 4 changes in return to education in terms of various attainments, among full-time salaried male workers during 1974–2007. The return to higher and secondary education apparently increased after the post-1974 trade liberalization period. However, the return to secondary education has persistently decreased since the mid-1980s and is now less than 10%; indeed, it is noteworthy that it decreased from 19.5% in 1985 to 7.5% in 2007. Thus, the decreasing trend of the return to secondary education in Chile, which was founded by each of in Contreras *et al* (1999) and Contreras (2002), has persisted since 1997. On the other hand, the return to higher education continued to increase following trade liberalization, reaching its peak in 1987, but slightly decreased thereafter; thus, changes in the return to higher education and the Gini of wages have seemed to move in the same direction. Overall, the return to primary education fluctuated by about 5%.

Figure 4. Changes in return to education by various attainments: full-time salaried male workers in Greater Santiago, 1974–2007



Source: Author’s calculations based on data from *Encuesta de Ocupación y desocupación en el Gran Santiago*.

Second, I compare the two measurements of return to education: that estimated by OLS using only full-time male salaried workers and that by Heckit using the full male sample including the unemployed, part-time workers and unpaid workers. The estimation results of Heckit are presented in Table A-1. Among the coefficients of the identifying variables, non-employment income is negative and statistically significant in most years, while the coefficients of the number of children under the age of 14 years in each household are not statistically significant in most years. The signs lack of consistency: they are positive in some years, but negative in others. Thus, we consider that the latter is not an appropriate identifying variable. Therefore, the low significance of those identifying variables in some years create high standard errors among the variables of the wage equation as estimated by Heckit, compared to that estimated by OLS. The coefficients of the inverse Mills ratio $\hat{\lambda}_i$ are positive in most years, except 1975 and 1982; they do have the expected signs, but they are not statistically significant at the 10% level, especially in the 1990s. Moreover, the coefficients of the years of schooling are positive and statistically significant in all the analyzing years; thus, more-educated individuals are actually more likely to be part of the full-time labor force.

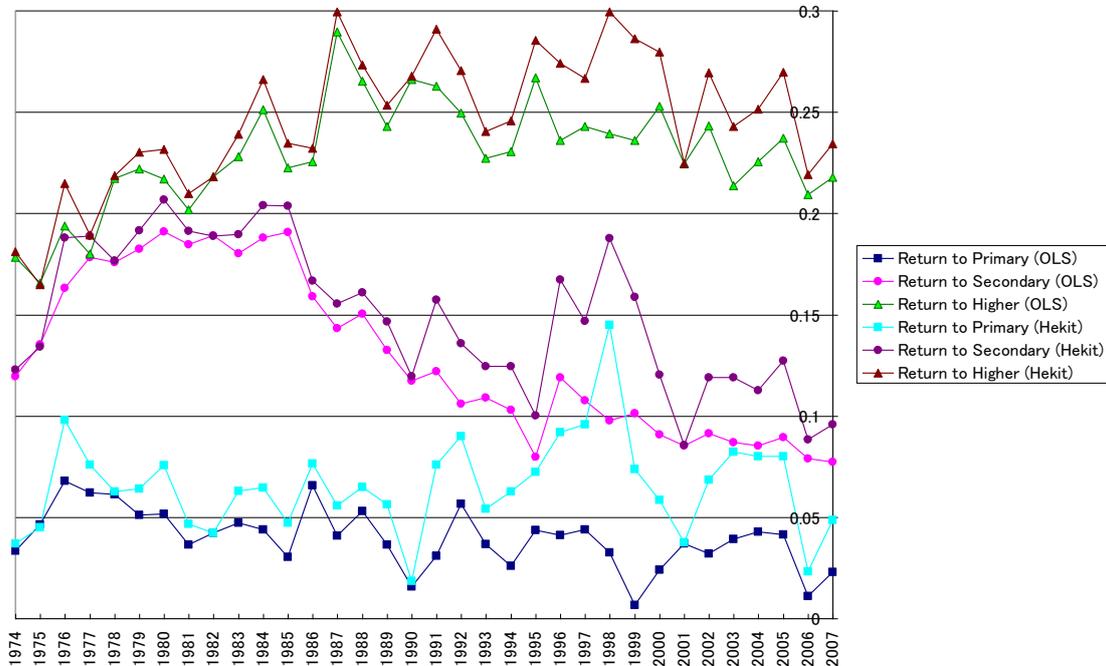
Therefore, those two findings—that the coefficients of the inverse Mills ratio are positive and that the coefficients of the years of schooling in the participation equation are positive—and the feature that the inverse Mills ratio is a monotonic decreasing function, lead to a larger return to education when estimated by Heckit than when estimated by OLS, except in 1975 and 1982.

Changes in the return to education in terms of various education attainments during 1974–2007, as estimated by both OLS and Heckit are presented in Figure 5. One of the most striking findings there is that differences between OLS and Heckit estimates are as small as 2% and are very stable until 1990, in spite of persistently high fluctuations in the unemployment rate during the 1970s and the 1980s; in comparison, differences are substantially large and greatly fluctuate in the mid-1990s, in spite of there being during the 1990s very low and stable unemployment rates (see Figure 1).¹⁸ However, the coefficients of years of schooling in most study years and the coefficients of the inverse Mills ratio in the 1990s are not statistically significant. Therefore, we must reject the assertion that there were sample selection biases during the aforementioned periods; thus, this issue can be ignored. On the other hand, the differences between OLS and Heckit estimates after 2002 are not practically small; there, the coefficients of years of schooling and of the inverse Mills ratio are statistically significant: when considering selection bias, the return to higher education increased, at most, by 3.2% in 2005. The large differences between OLS and Heckit estimates after 2002 can be attributed to relatively large coefficients of the inverse Mills ratio—that is, there was higher correlation between the error terms of the wage equation and the participation equation during that period (see Table A-1) and a relatively high unemployment rate after 1999 (see Figure 1).

In summary, OLS and Heckit estimates of the return to higher education tend to move precisely in the same direction up to 1990, and the differences between them in the mid-1990s are ignorable. However, the differences between OLS and Heckit estimates after 2002 are robust and not ignorable.

¹⁸ The ratios of the censored portions of the sample to the entire samples are larger than unemployment ratios, because not only unemployed but also part-time and unpaid workers are included in the sample for the participation equation, as explained in Section 3-2. However, they moved in precisely the same direction during 1974–2007.

Figure 5. Changes in return to education, by various attainments estimated by both OLS and Heckit in Greater Santiago, 1974–2007



Source: Author's calculations based on data from *Encuesta de Ocupación y desocupación en el Gran Santiago*.

Third, I compare changes in the Gini of wages and the return to higher education, as estimated by OLS and Heckit. Changes in the Gini of wages and the return to higher education as estimated by OLS, in both of which we have limited the samples to full-time salaried male workers during 1974–2007, are presented in Figure 6, while changes in the Gini of wages among full-time salaried male workers and the return to higher education estimated by Heckit are presented in Figure 7. The findings show that changes in the Gini of wages and the return to higher education estimated by both OLS and Heckit move precisely in the same direction up to the early 1990s, especially in the aftermath of trade liberalization. However, changes in the return to higher education as estimated by both OLS and Heckit tend to deviate from those of Gini of wages since the mid-1990s; especially, the decreasing trend of the Gini of wages after the 1990s is not evident in the Heckit estimates. However, the Heckit estimates in the 1990s lack statistical robustness, as mentioned, and we can see again that changes in Gini of wages and the return to higher education as estimated by Heckit tend to move in a similar direction after 2003, when the Heckit estimates are statistically significant. Therefore, it should not be overly problematic to use return to higher education as a measure of wage

inequality during the 1974–2007 period, although the decreasing trend of the Gini of wages after the 1990s is not as evident in the case of the return to higher education, in absolute terms.

Figure 6. Changes in the Gini of wages and return to higher education estimated by OLS: full-time salaried male workers in Greater Santiago, 1974–2007

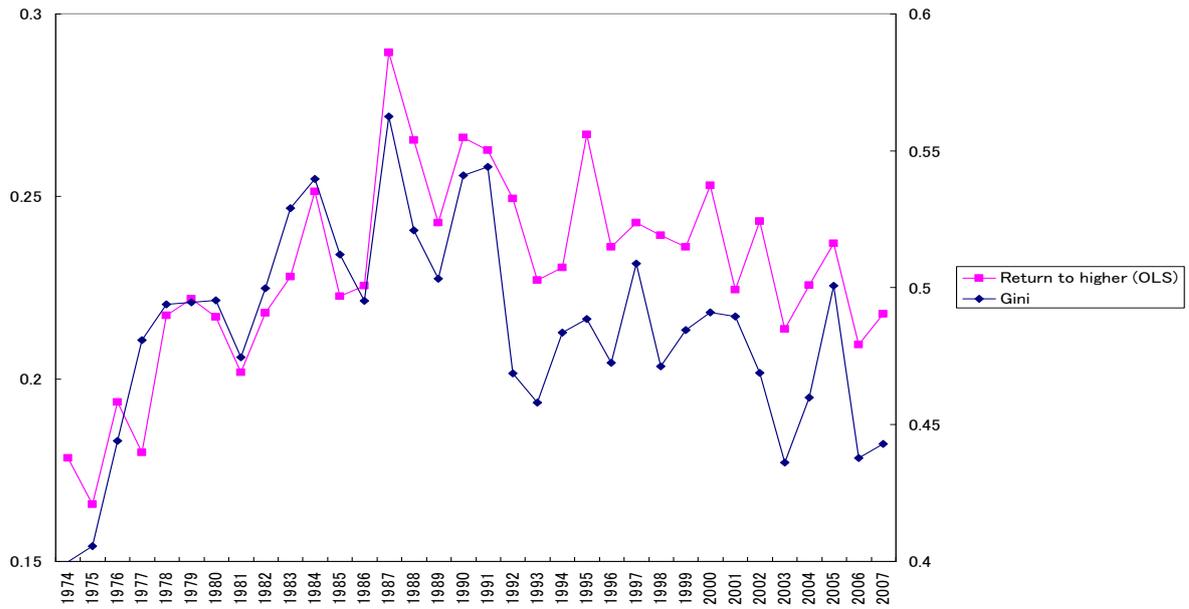
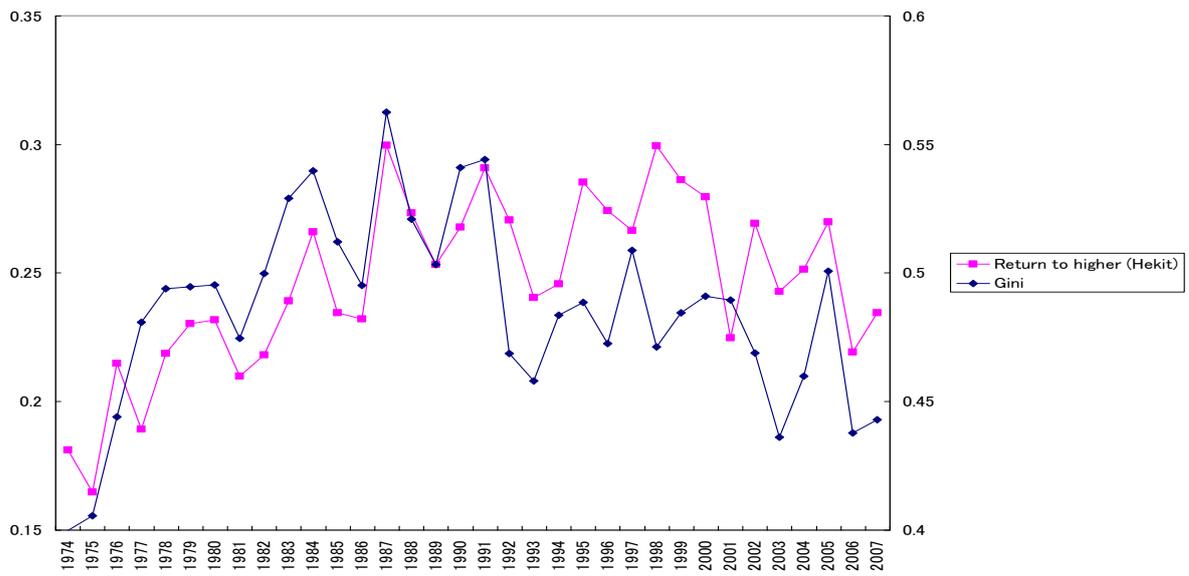


Figure 7. Changes in the Gini of wages (full-time salaried male workers) and the return to higher education estimated by Heckit in Greater Santiago, 1974–2007



Source: Author’s calculations based on data from *Encuesta de Ocupación y desocupación en el Gran Santiago*.

5. Conclusion

This study analyzed the validity of the return to higher education, an education-based measure of skill premium, as a measure of wage inequality, while taking into consideration sample selection bias; it uses data drawn from Chile during its trade liberalization period. The main findings are as follows. First, the return to higher education as estimated by OLS limiting the sample to full-time salaried male workers, and Heckit estimates tended to move precisely in the same direction up to 1990, especially in the aftermath of the trade liberalization, in spite of persistently and highly fluctuating unemployment rates during the 1970s and the 1980s. However, the return to higher education as estimated by Heckit was actually larger than those by OLS—at most 3%—as theoretically expected, in more recent periods after 2002. Second, changes in the return to higher education, as estimated by both OLS and Heckit, as well as other measures of wage inequality such as the Gini of wages, also tended to move in the same direction up to the early 1990s—that is, they increased significantly in the aftermath of the trade liberalization period, but substantially decreased during the early 1990s when trade liberalization had been sustained for some time and “reforms to the neoliberal reforms” were carried out. Thus, we confirmed—by using the return to higher education as a measure—that different periods of external reforms certainly produced different trends in wage inequality in Chile.

Therefore, I assert that the use of return to higher education as estimated by OLS—where the sample is limited to full-time salaried male workers—as a measure of wage inequality should not be problematic among data up to the early 1990s, especially in the aftermath of trade liberalization, although we need to be more cautious about the existence of selection bias in post-2002 data.

Further research needs to be done in this area. First, the number of children under than age of 14 years does not seem to be an appropriate identifying variable when analyzing male sample selection bias. Therefore, we involve a severe identification problem when the other identifying variable is not statistically significant in the participation equation. If I were to obtain an appropriate identifying variable that determines male labor force participation other than non-employment income, I could more precisely estimate the return to higher education, while taking into consideration sample selection bias. Second, this study cannot analyze why the return to higher education as estimated by Heckit has, since the 1990s, deviated from those estimated by OLS. The relatively large differences between OLS and Heckit estimates after 2002 can be attributed to the higher correlation between the error terms of the wage equation and those of the participation equation; this is because the differences in the periods are larger than in 1983, when the

unemployment rate was the highest.¹⁹ Therefore, the higher correlation between error terms of the wage equation and those of participation equation in recent years may reflect some kinds of changes within the Chilean labor market. One possible explanation is that the spread of higher education in a developing country is often associated with a general trend wherein an individual is more likely to participate in labor market, after controlling for the individual's education attainment. However, no such empirical analyses were undertaken in this study; this area will be an interesting subject for future research.

Acknowledgements

I am most grateful to the Microdata Center of the Department of Economics at the University of Chile, for providing data from *Encuesta de Ocupación y desocupación en el Gran Santiago* and to Prof. Esteban Puentes for answering my questions about interpreting that data. I am deeply grateful to Prof. Nobuaki Hamaguchi (Kobe University), Prof. Takahiro Sato (Kobe University), Prof. Matsushita Yukitoshi (Tsukuba University), Prof. Toru Yanagihara (Takushoku University), and Prof. Yoshiaki Hisamatsu (Toyo University) for providing insightful comments and suggestions.

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¹⁹ The difference between estimated by OLS and Heckit is only 1.1% in 1983, although unemployment rate was as high as 25.2% and the coefficient of the inverse Mills ratio is statistically significant.

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Appendix

Table A-1. Estimation Results of equation (3) by Heckman two-step procedure, 1974-2007.

	1974	1975	1976	1977	1978	1979	1980
Wage equation							
cons	4.5941 *** (0.2118)	4.5254 *** (0.2662)	3.5721 *** (0.6356)	4.2168 *** (0.2372)	4.7871 *** (0.1593)	4.6604 *** (0.1872)	4.3889 *** (0.2153)
years of schooling	0.0370 *** (0.0069)	0.0450 *** (0.0137)	0.0880 *** (0.0261)	0.0760 *** (0.0125)	0.0627 *** (0.0105)	0.0649 *** (0.0116)	0.0575 *** (0.0140)
exp	0.0325 *** (0.0061)	0.0291 *** (0.0068)	0.0571 *** (0.0123)	0.0540 *** (0.0068)	0.0456 *** (0.0057)	0.0515 *** (0.0053)	0.0507 *** (0.0063)
exp2	-0.0005 *** (0.0001)	-0.0004 *** (0.0001)	-0.0008 *** (0.0002)	-0.0008 *** (0.0001)	-0.0007 *** (0.0001)	-0.0008 *** (0.0001)	-0.0007 *** (0.0001)
d9*(school=9)	0.0858 *** (0.0168)	0.0891 *** (0.0163)	0.0899 *** (0.0221)	0.1129 *** (0.0184)	0.1140 *** (0.0179)	0.1273 *** (0.0175)	0.1311 *** (0.0187)
dt 2*(school=12)	0.0583 *** (0.0194)	0.0306 ** (0.0178)	0.0267 (0.0250)	0.0004 (0.0184)	0.0418 ** (0.0171)	0.0387 ** (0.0172)	0.0248 (0.0187)
Head of the household	0.2831 *** (0.0366)	0.2559 *** (0.0388)	0.1950 *** (0.0525)	0.2075 *** (0.0388)	0.2056 *** (0.0384)	0.2429 *** (0.0368)	0.2975 *** (0.0385)
Public Sectors	-0.0052 (0.0422)	-0.0086 (0.0411)	-0.1368 ** (0.0537)	-0.1773 *** (0.0440)	-0.2180 *** (0.0414)	-0.2006 *** (0.0422)	-0.2059 *** (0.0521)
Agriculture	-0.0969 (0.1022)	-0.0969 (0.1057)	0.0721 (0.1290)	-0.0320 (0.1087)	0.0334 (0.1082)	-0.2023 ** (0.1021)	-0.2489 ** (0.1229)
Mining	0.3419 ** (0.1498)	0.3196 ** (0.1371)	0.2951 (0.2533)	0.3795 ** (0.1874)	0.2798 * (0.1636)	0.0064 (0.1560)	0.1242 (0.1762)
NRBM	-0.0340 (0.0512)	-0.0183 (0.057)	-0.1175 (0.0755)	-0.0393 (0.0622)	0.0179 (0.0580)	-0.0731 (0.0580)	-0.0115 (0.0580)
Non-resource based manufacturing	0.0840 * (0.0438)	0.0308 (0.0482)	0.0091 (0.0674)	0.0495 (0.0542)	-0.0174 (0.0487)	0.0112 (0.0507)	0.0235 (0.053)
Commerce	-0.0346 (0.0554)	-0.0346 (0.0544)	-0.0346 (0.0751)	-0.0346 (0.0604)	-0.0346 * (0.0573)	-0.0346 (0.0560)	-0.0346 (0.0576)
Financial services	0.0108 (0.0645)	0.0309 (0.0615)	-0.0014 (0.0813)	0.1477 ** (0.0676)	-0.0656 (0.0594)	-0.0120 (0.0608)	0.1184 * (0.0671)
Personal services	-0.1507 ** (0.0649)	-0.1833 *** (0.0673)	-0.3037 *** (0.0801)	-0.0675 (0.0791)	-0.1166 * (0.0680)	-0.2562 *** (0.0689)	-0.2078 *** (0.0707)
Community services	-0.0764 (0.0607)	-0.1299 ** (0.0623)	-0.1640 * (0.0827)	-0.0036 (0.0672)	-0.0233 (0.0604)	-0.0701 * (0.0598)	-0.1789 *** (0.0653)
Transport	-0.0328 (0.0558)	-0.0328 (0.0587)	0.0721 (0.0788)	0.1740 *** (0.0641)	0.0552 (0.0581)	-0.0438 * (0.0606)	-0.0741 (0.0651)
Inverse Mills ratio	0.2134 (0.3053)	-0.0412 (0.2985)	0.9039 (0.7073)	0.5404 * (0.3002)	0.0931 (0.2089)	0.5166 ** (0.2584)	0.7225 *** (0.2688)
Participation equation							
cons	0.0705 (0.1373)	-0.2569 * (0.1344)	-0.3295 ** (0.1409)	-0.0997 (0.1420)	0.1439 (0.1427)	0.2349 * (0.1335)	-0.1068 (0.1584)
years of schooling	0.0474 *** (0.0093)	0.0792 *** (0.0089)	0.0707 *** (0.0090)	0.0697 *** (0.0090)	0.0693 *** (0.0091)	0.0657 *** (0.0088)	0.0612 *** (0.0108)
exp	0.0369 *** (0.0081)	0.0446 *** (0.0085)	0.0339 *** (0.0081)	0.0437 *** (0.0084)	0.0430 *** (0.0089)	0.0290 *** (0.0085)	0.0369 *** (0.0103)
exp2	-0.0005 *** (0.0002)	-0.0007 *** (0.0002)	-0.0004 ** (0.0002)	-0.0007 *** (0.0002)	-0.0008 *** (0.0002)	-0.0005 *** (0.0002)	-0.0005 ** (0.0002)
Non-employment income	-0.00492 *** (0.00140)	-0.01392 *** (0.00289)	-0.00183 ** (0.00617)	-0.00107 *** (0.00327)	-0.00103 *** (0.0020)	-0.00064 *** (0.0013)	-0.00434 *** (0.00693)
Numbers of children	0.0158 (0.0209)	-0.0199 (0.0202)	0.0098 (0.0219)	-0.0004 (0.0217)	0.0052 (0.0240)	-0.0438 * (0.0246)	-0.0038 (0.0285)
Number of obs	1885	2155	1962	2184	2159	2186	1887
Censored obs	367	460	485	431	390	410	311
Uncensored obs	1518	1695	1477	1753	1769	1776	1576
Return to primary education	0.0370	0.0450	0.0880	0.0760	0.0627	0.0641	0.0575
Return to secondary education	0.1228	0.1341	0.1890	0.1889	0.1767	0.1915	0.2068
Return to higher education	0.1811	0.1647	0.2147	0.1893	0.2186	0.2302	0.2316
Wage equation							
cons	4.9958 *** (0.2355)	5.1494 *** (0.3091)	4.3816 *** (0.251)	4.1380 *** (0.2250)	4.1485 *** (0.350)	4.3140 *** (0.2321)	4.3350 *** (0.307)
years of schooling	0.0467 *** (0.0179)	0.0422 ** (0.0192)	0.0628 *** (0.0134)	0.0645 *** (0.0166)	0.0472 *** (0.0170)	0.0755 *** (0.0182)	0.0556 * (0.0329)
exp	0.0499 *** (0.0094)	0.0480 *** (0.0055)	0.0548 *** (0.0064)	0.0526 *** (0.0067)	0.0661 *** (0.0071)	0.0426 *** (0.0068)	0.0453 *** (0.0161)
exp2	-0.0008 *** (0.0002)	-0.0007 *** (0.0001)	-0.0008 *** (0.0001)	-0.0007 *** (0.0001)	-0.0010 *** (0.0001)	-0.0005 *** (0.0001)	-0.0006 ** (0.0003)
d9*(school=9)	0.1447 *** (0.0288)	0.1467 *** (0.0233)	0.1268 *** (0.0210)	0.1383 *** (0.0196)	0.1505 *** (0.0186)	0.0805 *** (0.0200)	0.0987 *** (0.0203)
dt 2*(school=12)	0.0185 (0.0284)	0.0291 (0.0199)	0.0493 ** (0.0195)	0.0921 *** (0.0187)	0.0308 * (0.0175)	0.0652 *** (0.0170)	0.1442 *** (0.0179)
Head of the household	0.2196 *** (0.0616)	0.2213 *** (0.0453)	0.2015 *** (0.0454)	0.2462 *** (0.0435)	0.1471 *** (0.0407)	0.1571 *** (0.0411)	0.1717 *** (0.0411)
Public Sectors	-0.2685 *** (0.0823)	-0.3438 *** (0.0580)	-0.3085 *** (0.0526)	-0.2674 *** (0.0486)	-0.2277 *** (0.0474)	-0.2071 *** (0.0477)	-0.1759 *** (0.0514)
Agriculture	-0.4736 ** (0.2189)	-0.1708 (0.1838)	-0.0107 (0.2011)	-0.02 (0.1573)	-0.02 (0.1545)	0.1872 (0.1263)	-0.0545 (0.1446)
Mining	0.4050 (0.3431)	0.4818 ** (0.2107)	0.3087 (0.2556)	0.1119 (0.1922)	0.4496 *** (0.1698)	0.4632 *** (0.1564)	0.1980 (0.1473)
NRBM	-0.1659 ** (0.0835)	-0.0367 (0.0695)	0.0487 (0.0794)	0.0463 (0.0709)	-0.0181 (0.0711)	-0.0756 (0.0653)	0.0218 (0.0608)
Non-resource based manufacturing	-0.1450 * (0.0742)	0.0811 (0.0642)	0.0723 (0.0736)	0.0574 (0.0645)	-0.0417 (0.0601)	-0.0275 (0.0583)	0.0342 (0.0671)
Commerce	-0.2704 *** (0.0812)	-0.0206 (0.0648)	-0.1684 ** (0.0751)	-0.0898 (0.0675)	-0.1488 ** (0.0647)	-0.1738 *** (0.0619)	-0.1128 * (0.0591)
Financial services	-0.0821 (0.1001)	0.2472 *** (0.0721)	0.0898 (0.0787)	0.0995 (0.0679)	0.1651 ** (0.0674)	0.0866 (0.0673)	0.1898 *** (0.0678)
Personal services	-0.2973 *** (0.1103)	-0.1141 (0.0868)	-0.2453 *** (0.0843)	-0.1808 ** (0.0891)	-0.2013 *** (0.0773)	-0.2487 *** (0.0731)	-0.1476 ** (0.0751)
Community services	-0.1707 * (0.1027)	-0.0062 (0.0798)	0.0021 (0.0946)	0.0214 (0.0727)	-0.0762 (0.0696)	-0.0980 (0.0678)	-0.0782 (0.0685)
Transport	-0.1868 * (0.0860)	-0.0631 (0.0727)	-0.1825 ** (0.0831)	0.0364 (0.0726)	0.0142 (0.0679)	0.0648 (0.0691)	0.1356 ** (0.0657)
Inverse Mills ratio	1.1413 * (0.6295)	-0.0015 (0.2757)	0.5390 *** (0.1914)	0.6086 * (0.3325)	0.6345 (0.4547)	0.2862 (0.3478)	0.4988 (1.0329)
Participation equation							
cons	0.6969 *** (0.1591)	-0.5068 *** (0.1374)	-0.2428 * (0.1245)	-0.3318 ** (0.1432)	0.0241 (0.1437)	-0.2988 ** (0.1496)	-0.1357 (0.1524)
years of schooling	0.0291 *** (0.0105)	0.0876 *** (0.0088)	0.0553 *** (0.0087)	0.0696 *** (0.0093)	0.0551 *** (0.0089)	0.0742 *** (0.0098)	0.0645 *** (0.0102)
exp	0.0202 ** (0.0100)	0.0130 (0.0086)	0.0288 *** (0.0085)	0.0211 ** (0.0091)	0.0254 *** (0.0091)	0.0343 *** (0.0089)	0.0389 *** (0.0083)
exp2	-0.0004 * (0.0002)	-0.0001 (0.0002)	-0.0005 *** (0.0002)	-0.0003 (0.0002)	-0.0004 ** (0.0002)	-0.0006 *** (0.0002)	-0.0006 *** (0.0002)
Non-employment income	-0.00273 *** (0.00040)	-0.00174 *** (0.00044)	-0.00598 *** (0.00062)	-0.00141 *** (0.00043)	-0.00122 *** (0.00046)	-0.00112 *** (0.00046)	-0.00020 (0.00066)
Numbers of children	0.0168 (0.0299)	0.0224 (0.0238)	0.0056 (0.0250)	0.0517 * (0.0276)	-0.0172 (0.0257)	-0.0024 (0.0271)	-0.0154 (0.0288)
Number of obs	1963	1988	1968	1906	1942	1872	1862
Censored obs	258	639	635	509	427	444	355
Uncensored obs	1705	1349	1333	1397	1515	1428	1507
Return to primary education	0.0467	0.0422	0.0628	0.0645	0.0472	0.0765	0.0556
Return to secondary education	0.1313	0.1389	0.1827	0.0398	0.2037	0.1668	0.1554
Return to higher education	0.2089	0.2180	0.2390	0.2659	0.2345	0.2320	0.2985

	1988	1989	1990	1991	1992	1993	1994
Wage equation							
cons	4.2041 *** (0.4067)	4.5772 *** (0.5764)	5.2454 *** (0.6111)	4.1094 *** (1.5537)	4.3773 *** (0.6977)	4.8627 *** (0.7850)	5.0984 *** (0.7675)
years of schooling	0.0648 *** (0.0177)	0.0562 * (0.0294)	0.0186 (0.0293)	0.0760 (0.0708)	0.0900 ** (0.0444)	0.0542 (0.0351)	0.0626 (0.0478)
exp	0.0413 *** (0.0107)	0.0429 *** (0.0141)	0.0268 *** (0.0088)	0.0400 (0.0293)	0.0297 * (0.0163)	0.0448 * (0.0236)	0.0347 ** (0.0161)
exp2	-0.0005 *** (0.0002)	-0.0006 ** (0.0003)	-0.0004 *** (0.0001)	-0.0005 (0.0005)	-0.0003 (0.0003)	-0.0006 (0.0004)	-0.0005 * (0.0003)
d9*(school-9)	0.0961 *** (0.0196)	0.0929 *** (0.0207)	0.1010 *** (0.0227)	0.0814 * (0.0442)	0.0457 (0.0560)	0.0702 (0.0434)	0.0619 (0.0404)
dl2*(school-12)	0.1124 *** (0.0176)	0.1067 *** (0.0171)	0.1462 *** (0.0174)	0.1334 *** (0.0364)	0.1348 *** (0.0494)	0.1160 *** (0.0345)	0.1212 *** (0.0305)
Head of the household	0.1961 *** (0.0406)	0.0856 ** (0.0383)	0.2206 *** (0.0391)	0.1717 ** (0.0808)	0.1725 (0.1083)	0.1336 * (0.0804)	0.1828 ** (0.0729)
Public Sectors	-0.1107 ** (0.0537)	-0.0839 (0.0509)	-0.1329 ** (0.0547)	-0.0374 (0.1242)	-0.0214 (0.1225)	-0.1471 (0.1284)	-0.1456 (0.1056)
Agriculture	0.1649 (0.1457)	-0.0123 (0.1482)	0.0066 (0.1635)	0.0648 (0.4306)	-0.0293 (0.3676)	-0.3511 (0.3461)	-0.1911 (0.2828)
Mining	0.6655 *** (0.1589)	0.5364 *** (0.1555)	0.3313 ** (0.1536)	0.8217 ** (0.3619)	0.6896 (0.4518)	0.0302 (0.4909)	0.1018 (0.3607)
NRBM	0.0646 (0.0595)	0.0023 (0.0572)	-0.0463 (0.0645)	0.0299 (0.1283)	0.0416 (0.1690)	-0.0865 (0.1192)	-0.1394 (0.1070)
Non-resource based manufacturing	0.0110 *** (0.0526)	0.0764 (0.0513)	-0.0230 (0.0578)	-0.0823 (0.1110)	-0.0236 (0.1402)	-0.0236 (0.1061)	-0.1129 (0.0953)
Commerce	0.1432 ** (0.0594)	0.0288 (0.0547)	-0.0698 (0.0624)	-0.0155 (0.1245)	-0.0890 (0.1574)	-0.1373 (0.1144)	-0.1876 * (0.1052)
Financial services	0.3162 *** (0.0648)	0.2908 *** (0.0664)	0.2825 *** (0.0689)	0.2537 * (0.1365)	0.2464 (0.1858)	0.1996 (0.1318)	0.1601 (0.1174)
Personal services	-0.1003 (0.0729)	-0.0293 (0.0731)	-0.0448 (0.0789)	-0.0897 (0.1507)	-0.0856 (0.2076)	-0.1898 (0.1777)	-0.2287 * (0.1336)
Community services	-0.0586 (0.0695)	-0.1414 ** (0.0680)	-0.1401 *** (0.0711)	-0.0309 (0.1433)	-0.2498 (0.1937)	-0.2630 * (0.1377)	-0.2454 ** (0.1193)
Transport	0.1508 ** (0.0635)	0.0872 (0.0626)	0.0877 (0.0651)	0.0455 (0.1330)	-0.0035 (0.1693)	-0.1166 (0.1227)	-0.1056 (0.1130)
Inverse Mills ratio	0.5422 (0.5797)	0.6195 (0.8441)	0.0891 (0.7962)	1.5172 (2.2211)	1.9153 (1.4662)	1.4291 (1.6874)	1.2091 (1.3693)
Participation equation							
cons	0.0465 (0.1610)	-0.0444 (0.1859)	-0.0768 (0.1741)	-0.0909 (0.1640)	0.5575 *** (0.2044)	0.3995 ** (0.1864)	0.2096 (0.2121)
years of schooling	0.0536 *** (0.0107)	0.0782 *** (0.0122)	0.0768 *** (0.0122)	0.0732 *** (0.0107)	0.0585 *** (0.0135)	0.0435 *** (0.0122)	0.0812 *** (0.0144)
exp	0.0447 *** (0.0095)	0.0491 *** (0.0111)	0.0291 *** (0.0099)	0.0375 *** (0.0099)	0.0235 * (0.0122)	0.0457 *** (0.0113)	0.0382 *** (0.0119)
exp2	-0.0007 *** (0.0002)	-0.0009 *** (0.0002)	-0.0004 * (0.0002)	-0.0006 *** (0.0002)	-0.0003 (0.0002)	-0.0007 *** (0.0002)	-0.0007 *** (0.0002)
Non-employment income	-0.00036 * (0.00021)	-0.00015 (0.00018)	-0.00005 (0.00004)	-0.00005 (0.00010)	-0.00019 * (0.00011)	-0.00006 (0.00004)	-0.00014 ** (0.00008)
Numbers of children	-0.0335 (0.0294)	-0.0098 (0.0338)	0.0153 (0.0339)	0.0007 (0.0329)	-0.0753 ** (0.0380)	-0.0068 (0.0401)	-0.0050 (0.0429)
Number of obs	1826	1748	1761	1854	1712	1758	1632
Censored obs	305	215	251	264	153	164	139
Uncensored obs	1521	1533	1510	1590	1559	1594	1493
Return to primary education	0.0648	0.0582	0.0186	0.0760	0.0900	0.0542	0.0626
Return to secondary education	0.1610	0.1465	0.1196	0.1574	0.1357	0.1244	0.1246
Return to higher education	0.2733	0.2532	0.2677	0.2908	0.2705	0.2404	0.2458

	1995	1996	1997	1998	1999	2000	2001
Wage equation							
cons	4.8544 ** (2.0347)	4.2381 ** (2.1267)	4.6114 *** (0.9384)	3.8886 * (2.0517)	4.1749 * (2.4681)	4.8282 *** (0.7361)	5.7850 *** (0.3017)
years of schooling	0.0723 (0.0809)	0.0920 (0.0830)	0.0958 * (0.0563)	0.1448 (0.1208)	0.0736 (0.1003)	0.0585 * (0.0330)	0.0376 ** (0.0176)
exp	0.0514 (0.0613)	0.0557 (0.0476)	0.0395 ** (0.0189)	0.0484 * (0.0293)	0.0468 (0.0374)	0.0450 *** (0.0150)	0.0176 * (0.0084)
exp2	-0.0008 (0.0008)	-0.0008 (0.0008)	-0.0008 (0.0003)	-0.0005 (0.0005)	-0.0006 (0.0005)	-0.0006 *** (0.0003)	-0.0002 (0.0003)
d9*(school-9)	0.0280 (0.0679)	0.0752 (0.0865)	0.0509 (0.0510)	0.0430 (0.0939)	0.0851 * (0.0466)	0.0619 ** (0.0260)	0.0481 ** (0.0232)
dl2*(school-12)	0.1850 *** (0.0445)	0.1070 (0.0669)	0.1198 *** (0.0432)	0.1117 (0.0770)	0.1275 *** (0.0355)	0.1591 *** (0.0212)	0.1391 *** (0.0160)
Head of the household	0.1200 (0.1066)	0.1487 (0.1570)	0.1928 * (0.1020)	0.1930 (0.1743)	0.3025 *** (0.0852)	0.1738 *** (0.0512)	0.2085 *** (0.0369)
Public Sectors	-0.0337 (0.1822)	-0.0313 (0.2821)	-0.1121 (0.1675)	-0.1801 (0.2720)	0.0084 (0.1399)	-0.1351 * (0.0781)	-0.1183 ** (0.0592)
Agriculture	-0.4489 (0.4561)	-0.3896 (0.7394)	0.1063 (0.4250)	-0.2427 (0.6479)	-0.0055 (0.2865)	-0.2551 (0.1870)	-0.0819 (0.1703)
Mining	0.4385 (0.4467)	0.3125 (0.6619)	0.0970 (0.4857)	0.0748 (0.8503)	0.2690 (0.3931)	0.3731 (0.2482)	0.2231 (0.1833)
NRBM	-0.1219 (0.1535)	-0.2099 (0.2373)	-0.0573 (0.1469)	-0.0694 (0.2585)	-0.0538 (0.1307)	-0.0287 (0.0800)	-0.1016 * (0.0582)
Non-resource based manufacturing	-0.0812 (0.1456)	-0.0695 (0.2174)	0.0367 (0.1284)	-0.1074 (0.2299)	-0.0385 (0.1228)	-0.0853 (0.0749)	-0.2286 ** (0.0536)
Commerce	-0.1709 (0.1441)	-0.2347 (0.2192)	-0.0989 (0.1325)	-0.0968 (0.2271)	-0.1294 (0.1228)	-0.0999 (0.0753)	-0.1922 *** (0.0523)
Financial services	0.1307 (0.1618)	-0.0030 (0.2511)	0.1357 (0.1529)	0.0691 (0.2484)	0.0579 (0.1324)	0.0706 (0.0793)	0.0583 (0.0559)
Personal services	-0.2968 (0.1509)	-0.1799 (0.2373)	-0.1328 (0.1469)	-0.3067 (0.2585)	-0.3134 * (0.1307)	-0.3483 *** (0.0800)	-0.3398 *** (0.0582)
Community services	-0.3383 * (0.1757)	-0.3109 (0.2569)	-0.1139 (0.1607)	-0.1475 (0.2861)	-0.2609 * (0.1457)	-0.0782 (0.0859)	-0.1299 ** (0.0642)
Transport	-0.1505 (0.1637)	-0.1175 (0.2552)	0.0793 (0.1502)	-0.1048 (0.2574)	-0.1247 (0.1347)	0.0032 (0.0801)	-0.1147 * (0.0592)
Inverse Mills ratio	1.7643 (4.5124)	2.6487 (3.7294)	1.6586 (1.4521)	3.1335 (2.9234)	1.5965 (2.2793)	0.9802 (0.7360)	0.0278 (0.2949)
Participation equation							
cons	0.4841 ** (0.1896)	0.1083 (0.1860)	-0.0148 (0.2047)	-0.1967 (0.1813)	-0.6912 *** (0.1550)	-0.6071 *** (0.1582)	-0.3530 ** (0.1522)
years of schooling	0.0473 *** (0.0134)	0.0613 *** (0.0123)	0.0863 *** (0.0136)	0.0991 *** (0.0122)	0.0816 *** (0.0101)	0.0757 *** (0.0104)	0.0456 *** (0.0101)
exp	0.0405 *** (0.0120)	0.0382 *** (0.0109)	0.0332 *** (0.0115)	0.0287 *** (0.0107)	0.0361 *** (0.0085)	0.0391 *** (0.0083)	0.0617 *** (0.0081)
exp2	-0.0007 *** (0.0002)	-0.0005 ** (0.0002)	-0.0005 ** (0.0002)	-0.0002 (0.0002)	-0.0004 ** (0.0002)	-0.0006 *** (0.0002)	-0.0011 *** (0.0002)
Non-employment income	-0.00001 (0.00008)	-0.00004 (0.00004)	-0.00008 ** (0.00004)	-0.00008 ** (0.00004)	-0.0000001 (0.0000)	0.0000000 (0.0000)	-0.0000008 *** (0.0000)
Numbers of children	-0.0162 (0.0430)	0.0223 (0.0883)	0.0282 (0.0407)	-0.0143 (0.0362)	0.0058 (0.0297)	0.0629 ** (0.0300)	-0.0095 (0.0289)
Number of obs	1565	1556	1592	1861	1888	1956	2003
Censored obs	140	178	163	201	470	445	486
Uncensored obs	1425	1378	1429	1660	1418	1511	1516
Return to primary education	0.0723	0.0820	0.0958	0.1448	0.0736	0.0585	0.0376
Return to secondary education	0.1003	0.1672	0.1467	0.1878	0.1587	0.1204	0.0857
Return to higher education	0.2853	0.2741	0.2665	0.2895	0.2861	0.2795	0.2248

	2002	2003	2004	2005	2006	2007
Wage equation						
cons	4.6390 *** (0.5255)	4.4991 *** (0.7738)	4.7337 *** (0.5462)	4.1711 *** (0.7448)	5.4805 *** (0.3314)	5.2798 *** (0.3808)
years of schooling	0.0683 ** (0.0294)	0.0823 ** (0.0384)	0.0800 *** (0.0301)	0.0800 * (0.0428)	0.0233 (0.0200)	0.0486 ** (0.0232)
exp	0.0563 *** (0.0156)	0.0510 *** (0.0188)	0.0342 *** (0.0120)	0.0602 *** (0.0208)	0.0360 *** (0.0102)	0.0358 *** (0.0109)
exp2	-0.0009 *** (0.0003)	-0.0007 ** (0.0003)	-0.0004 * (0.0002)	-0.0008 ** (0.0003)	-0.0005 *** (0.0002)	-0.0005 *** (0.0002)
d8*(school-8)	0.0505 (0.0363)	0.0368 (0.0389)	0.025 (0.0341)	0.0474 (0.0557)	0.0651 ** (0.0273)	0.0472 * (0.0265)
dt2*(school-12)	0.1504 *** (0.0284)	0.1237 *** (0.0284)	0.1389 *** (0.0240)	0.1424 *** (0.0409)	0.1309 *** (0.0201)	0.1385 *** (0.0175)
Head of the household	0.1512 ** (0.0653)	0.1449 ** (0.0686)	0.2168 *** (0.0543)	0.2196 ** (0.0818)	0.2155 *** (0.0471)	0.2035 *** (0.0416)
Public Sectors	0.0688 (0.1040)	-0.0245 (0.1149)	0.0421 (0.0850)	0.0594 (0.1472)	0.0751 (0.0767)	-0.0361 (0.0718)
Agriculture	-0.2221 (0.2183)	-0.0523 (0.2318)	-0.1338 (0.1870)	0.0708 (0.4334)	-0.2856 (0.2005)	-0.0389 (0.1665)
Mining	0.5893 (0.3598)	0.4725 (0.3266)	0.7902 *** (0.2352)	0.5859 (0.3806)	0.0045 (0.2583)	0.1939 (0.1868)
NRBM	-0.1347 (0.1052)	-0.1121 (0.1113)	-0.0712 (0.0858)	0.0857 (0.1577)	-0.1922 *** (0.0705)	-0.0824 (0.0718)
Non-resource based manufacturing	-0.1624 * (0.0973)	0.0135 (0.1057)	-0.0618 (0.0804)	0.0105 (0.1365)	-0.0367 (0.0682)	-0.0667 (0.0637)
Commerce	-0.1748 * (0.0974)	-0.0738 (0.1025)	-0.0824 (0.0766)	-0.0859 (0.1262)	-0.1987 *** (0.0620)	-0.0955 * (0.0539)
Financial services	-0.0248 (0.1054)	0.0668 (0.1084)	-0.0065 (0.0855)	0.0799 (0.1379)	0.0076 (0.0677)	0.0363 (0.0624)
Personal services	-0.1680 (0.1306)	-0.2148 (0.1388)	-0.2960 *** (0.1053)	-0.1248 (0.1771)	-0.2671 *** (0.0857)	-0.1254 (0.0807)
Community services	-0.1733 (0.1119)	-0.0168 (0.1162)	-0.0468 (0.0933)	-0.0898 (0.1518)	-0.2576 *** (0.0798)	-0.0546 (0.0667)
Transport	-0.1735 (0.1084)	-0.0656 (0.1061)	-0.1134 (0.0824)	-0.0409 (0.1402)	-0.0705 (0.0691)	0.0693 (0.0595)
Inverse Mills ratio	1.3295 ** (0.5446)	1.3600 (0.6379)	1.0842 ** (0.5544)	1.7847 ** (0.8295)	0.8921 ** (0.4248)	0.8083 ** (0.4046)
Participation equation						
cons	-0.3886 ** (0.1558)	-0.4516 *** (0.1637)	-0.5509 *** (0.1590)	-0.4466 *** (0.1652)	0.0128 (0.1677)	-0.5478 *** (0.1877)
years of schooling	0.0605 *** (0.0104)	0.0713 *** (0.0108)	0.0741 *** (0.0107)	0.0646 *** (0.0113)	0.0353 *** (0.0112)	0.0776 *** (0.0125)
exp	0.0525 *** (0.0081)	0.0471 *** (0.0083)	0.0414 *** (0.0080)	0.0492 *** (0.0082)	0.0495 *** (0.0082)	0.0655 *** (0.0083)
exp2	-0.0009 *** (0.0002)	-0.0007 *** (0.0002)	-0.0005 *** (0.0002)	-0.0006 *** (0.0002)	-0.0007 *** (0.0002)	-0.0010 *** (0.0002)
Non-employment income	-0.0000010 *** (0.0000)	-0.0000008 ** (0.0000)	-0.0000006 ** (0.0000)	-0.0000006 *** (0.0000)	-0.0000008 *** (0.0000)	-0.0000007 *** (0.0000)
Numbers of children	0.0309 (0.0307)	0.0480 (0.0326)	0.0565 * (0.0333)	0.0822 ** (0.0385)	-0.0181 (0.0351)	0.0247 (0.0357)
Number of obs	2037	2044	1976	1984	1842	2021
Censored obs	444	385	405	363	363	315
Uncensored obs	1593	1659	1571	1621	1579	1706
Return to primary education	0.0683	0.0623	0.0800	0.0800	0.0233	0.0486
Return to secondary education	0.1188	0.1191	0.1125	0.1274	0.0884	0.0859
Return to higher education	0.2692	0.2428	0.2514	0.2697	0.2193	0.2344

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Note: Numbers in parenthesis are standard errors.