

**From Public to Private:  
The Performance of Former Public Workers in the Brazilian Labor Market\***

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**Abstract**

This paper analyzes the placement in the private sector of a subset of Brazilian public-sector employees. This group left public employment in the mid-1990's through a voluntary severance program. This paper contrasts their earnings before and after quitting the public sector, and compares both sets of wages to public and private sector earnings for similar workers. We find that participants in this voluntary severance program suffered a significant reduction in average earnings wage and an increase in earnings dispersion. We test whether the reduction in average earnings and the increase in earnings dispersion is the expected outcome once one controls for observed characteristics, by means of counterfactual simulations. Several methods of controlling for observed characteristics (parametric and non-parametrically) are used for robustness. The results indicate that this group of workers was paid at levels below what would be expected given their embodied observable characteristics.

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## I. Introduction

Mainly forced by a chronic public deficit problem, the Brazilian federal government exerted substantial efforts to reduce the number of public servants in the second half of the 1990's. In some cases, the government was concerned with the social welfare impact of such major layoffs. In fact, the design of an efficient public sector downsizing program depends heavily on an estimation of the capacity of the private sector to absorb former public workers.<sup>1</sup>

Given the existing legal constraints on firing public workers and an overall opposition to public sector reform in Brazil, the federal government typically opted for voluntary job retrenchment schemes. Many state firms, in a step towards privatization, promoted the so-called Voluntary Severance Programs (*Programas de Demissão Voluntária*, PDV), which gave monetary incentives to workers who quit their jobs.<sup>2</sup> In a developing country like Brazil, characterized by overstaffing, it is expected that PDV's result in an adverse selection outcome, with the best workers, those with higher reservation wages, opting to leave. On the other hand, the fact that these workers usually have very specific human capital, combined with a possible stigma effect, can reduce both the probability of absorption and expected earnings in the private sector.

In 1995, *Rede Ferroviária Federal S.A.* (RFFSA), a huge public firm that had the monopoly on all Brazilian railways, adopted a PDV. From 1995 to the end of 1997 more than 7,000 workers joined the program, while many others opted for early retirement. A first survey with those former employees at RFFSA was conducted in March 1998.<sup>3</sup> It revealed that their reinsertion in the private labor market was not a success, although many workers were absorbed by the private sector.

Figure 1 below is the main motivation for this paper. It gives a striking picture of the performance of these former public workers, by summarizing the distributions of real earnings of previous RFFSA workers before and after leaving the firm. The picture shows that average real earnings dropped by 15,4%, while earnings inequality dramatically increased. In fact, 72% of these workers observed reductions in real earnings.<sup>4</sup> A significant proportion (31%) of these workers were receiving less than R\$300,00 (2,5 times the minimum wage) in the private sector in 1997. This contrasts with a very small proportion (0,16%) of these workers that were in this earnings range in 1995, while at RFFSA.

These results are in a certain way expected. It is a well-documented fact that Brazilian public employees earn on average more than workers at the private sector (see Foguel *et al.*, 2000). On the other hand, a comparison between public and private sectors in Brazil and other Latin American countries reveals that wage inequality among workers in the private sector is typically significantly higher than among public employees (see Panizza and Qiang, 2000). Therefore, it is also not surprising that the earnings distribution widened among these former public employees. The interesting comparison, however, is with the expected earnings distributions of these workers in the private sector, given their observable characteristics.

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<sup>1</sup> See Rama (1999) for a survey of several studies on public sector downsizing.

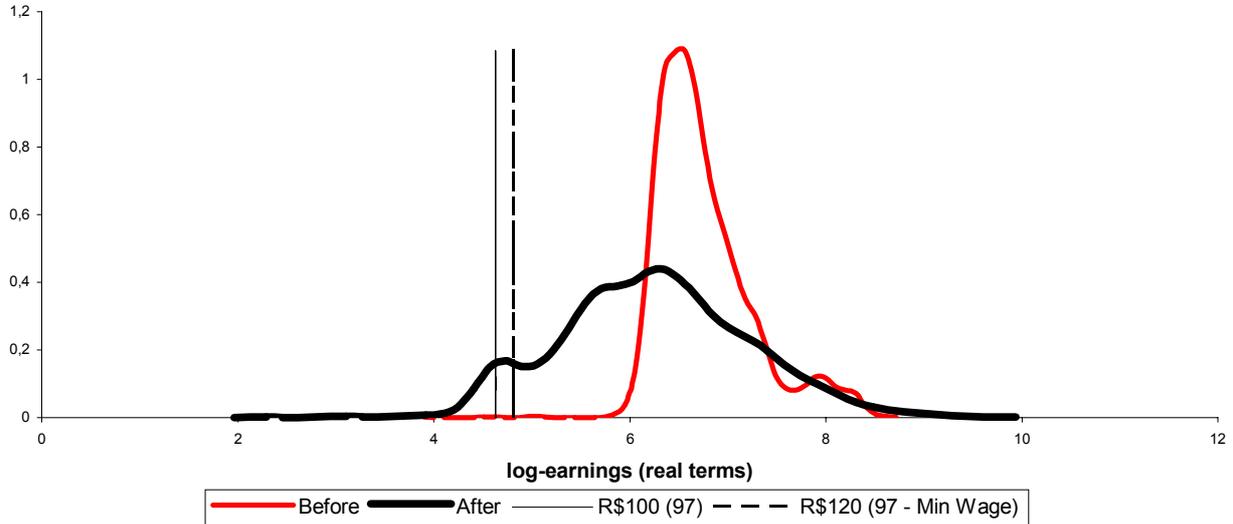
<sup>2</sup> In fact, PDV's were also applied at the federal administrative level and by many states, targeting a variety of workers and locations. Particular emphasis, however, was given to state enterprises, since the government had a special interest in privatizing some of these firms and needed a fast payroll reduction. See Carneiro and Gill (1999) for a description of public sector downsizing programs in Brazil.

<sup>3</sup> The details of that survey are described in Section II and more fully in Amadeo, Camargo and Gonzaga (1998).

<sup>4</sup> Most workers (80%) changed occupations. In fact, 45% of them became self-employed, while other 20% started their own business, hiring employees.

**Figure 1**

**Log-earnings density function - REDE Employees:  
before and after leaving public sector**



The main objective of this paper is to compare the outcomes of the former RFFSA employees with those in the public and private sectors in Brazil. We investigate how have these workers performed in the private sector, once we take into consideration their observable attributes. Have they converged to a similar earnings distribution prevailing in that sector, given their observable characteristics? In order to study the process of absorption by the private sector of these workers, we use the RFFSA survey data set, in combination with information from national household surveys. Our decomposition analysis attempts to identify the role of observable characteristics, as well as their remuneration in the public and the private sector, in explaining the observed changes in the earning distributions of the former RFFSA employees. In order to deal with selection bias, we control for observable characteristics, using parametric, semi-parametric and non-parametric methods. The idea is to test how robust are the results with respect to the choice of matching techniques.

The paper is organized as follows. The next section describes the data. Section III presents the gross earnings gaps observed for the distributions used in the paper. Section IV discusses the research methodology. Section V presents and interprets the empirical results. Section VI concludes.

## **II. Data description**

Two data sets are used in this study. The first one, henceforth referred as REDE, contains information on more than 5,000 workers out of around 7,000 who left their jobs at RFFSA through the Voluntary Severance Program from 1995 to 1997. The survey was conducted in March 1998 and collected data on several labor market variables, including earnings, employment status, and duration of unemployment and employment spells. It has information on schooling levels, grouped into nine categories, which correspond to the following ranges of years of schooling: 0-3, 4, 5-7, 8,

9-10, 11, 12-14, 15, and more than 15.<sup>5</sup> REDE also contains official administrative information for all workers who joined the PDV, including their last wages at RFFSA.

The other data set, *Pesquisa Nacional de Amostra por Domicilio* (PNAD), is the annual Brazilian Household Survey, collected by IBGE. PNAD covers the whole country, with the exception of some rural areas. It is the largest and most important Brazilian household survey, interviewing more than 75,000 households every year, which corresponds to about 300,000 individuals. PNAD collects data every September since 1976, with the exception of Census years and a couple of other years. It contains information on labor, demographic, educational and regional variables and has been widely used in many micro-econometric studies.

In this study, we use information from both data sets for men in the age range of 25-64 and with a paid main activity that requires at least 20 weekly hours of work.<sup>6</sup> Two yearly editions of PNAD were selected, 1995 and 1997. These two years were chosen in order to approximately match both the timing of exit from RFFSA and the absorption of these workers by the private sector, as captured by the REDE survey.

Data on earnings correspond to positive monthly labor earnings on the main activity. This variable was properly deflated and evaluated at March 1998, the date of the REDE survey. In the PNAD data set, outliers (earnings larger than R\$ 250,000 a month) are not considered in the analysis. In the REDE data set, we only use information about workers who switched to the private sector after quitting, as answered in the survey of March 1998.

Since REDE is restricted to some Federation States, only observations in the same geographical range are used in PNAD. In practice, this means that the North Region and some States in the Mid-West are not considered here. We also exclude data from rural areas and for workers in agricultural activities. Finally, the classification at PNAD for a job at the public sector has the broadest sense, meaning that not only federal public servants are considered as working in the public sector but also any individual who declared to work at that sector with or without a formal labor contract.

Table 1 displays summary statistics for the most important variables in the two data sets and the number of observations remaining after the application of the filters described above.<sup>7</sup> Note that Rede workers are, on average, older, more educated and more concentrated in the Southeast region of the country than public and private workers (see also Figures 2a to 2d).

### III. Total Earnings Gap

In this section, we analyze the average total earnings gap for the RFFSA workers that were absorbed by the private sector and decompose it into several parts. As described in the previous section, we have information on real earnings,  $y_{i,t,s,p}$ , for each individual  $i$ , at time  $t$  (1995 and 1997), at sector  $s$  (public and private), and for both available data sets  $p$  (REDE and PNAD). Considering the transformation to log-earnings,  $w_{i,t,s,p} = \log(y_{i,t,s,p})$ , we have six distributions of log-earnings that can be used, since for REDE individuals we only have two possibilities: one was either in the private sector in 1997 or in the public sector in 1995. To fix notation, let us say that an individual  $i$  is in market  $m$  when he faces a triple  $(t,s,p)$ .

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<sup>5</sup> In fact, there are ten categories but the first two (illiteracy and less than four years of schooling) were merged into one group here. The categories corresponding to isolated years (4, 8, 11 and 15) reflect the attainment of some school degree in Brazil (elementary, medium, high school and college, respectively).

<sup>6</sup> We restricted our attention to male workers since more than 91% of those former workers who entered the private sector are men.

<sup>7</sup> Note that in Table 1 the reported values for age for workers from REDE data set are these prevailing in 1995.

In this paper, the main interest is in the difference between some parameters of two distributions in particular: workers that we observe in 1997 at the private sector using REDE data set and workers that we observe in 1995 at the public sector using REDE data set. For the particular case of those two distributions, let us say that a worker is in the labor market  $m = 1$  if we observe him in the former distribution (1997, private, REDE) and that he is in the labor market  $m = 0$  if we observe him in the latter (1995, public, REDE). It turns out that because of panel features of REDE data set, those workers are the same in both distributions.

The gross total earnings gap is given by  $E[w_1] - E[w_0]$ . Many additional insights can be brought by using a third distribution,  $w_2$ , and noting that the difference in means,  $E[w_1] - E[w_0]$ , can be decomposed into the sum of two differences  $(E[w_1] - E[w_2]) + (E[w_2] - E[w_0])$ . This decomposition in differences method allows one to split the differences in parameters of two specific distributions into several distinct partial effects.

It is possible to decompose the difference between the distributions (1997, private, REDE) and (1995, public, REDE) into 4 intermediate differences. For example, one could compare the earnings distribution of former RFFSA employees with the earnings distribution of all private sector workers in 1997; then examine how the private sector earnings distribution evolved between 1995 and 1997; and finally compare the distributions of the public and the private sectors in 1995. In fact, there are two ways of decomposing the total earnings gap into 4 intermediate differences, which are described below:

$$E[w_{1997, \text{private, REDE}}] - E[w_{1995, \text{public, REDE}}] =$$

Case 1:

$$\begin{aligned} &= E[w_{1997, \text{private, REDE}}] - E[w_{1997, \text{private, PNAD}}] && \text{(step 1)} \\ &+ E[w_{1997, \text{private, PNAD}}] - E[w_{1997, \text{public, PNAD}}] && \text{(step 2)} \\ &+ E[w_{1997, \text{public, PNAD}}] - E[w_{1995, \text{public, PNAD}}] && \text{(step 3)} \\ &+ E[w_{1995, \text{public, PNAD}}] - E[w_{1995, \text{public, REDE}}] && \text{(step 4)} \end{aligned}$$

Case 2:

$$\begin{aligned} &= E[w_{1997, \text{private, REDE}}] - E[w_{1997, \text{private, PNAD}}] && \text{(step 1, same as in Case 1)} \\ &+ E[w_{1997, \text{private, PNAD}}] - E[w_{1995, \text{private, PNAD}}] && \text{(step 2)} \\ &+ E[w_{1995, \text{private, PNAD}}] - E[w_{1995, \text{public, PNAD}}] && \text{(step 3)} \\ &+ E[w_{1995, \text{public, PNAD}}] - E[w_{1995, \text{public, REDE}}] && \text{(step 4, same as in Case 1)} \end{aligned}$$

The difference between cases 1 and 2 is in steps 2 and 3. In case 1, step 3 measures the evolution of public sector earnings between 1995 and 1997, while step 2 compares the private and the public sector in 1997. In case 2, step 3 measures the difference between the public and the private sector in 1995, while step 2 captures the temporal evolution of private sector earnings.

Table 2 summarizes the results of these mean decompositions for all steps in case 1.<sup>8</sup>

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<sup>8</sup> Case 2 results are not reported here. In fact, these results do not bring interesting insights, since the structure of both public and private sector wages did not change much between 1995 and 1997.

## IV. Research Methodology

In this section, we describe our methodological approach discussing several ways to estimate controlled wage gaps and the assumptions needed for consistency for each estimator in consideration.

### IV.1 The controlled earnings gap and the average treatment effect

Our goal is to estimate the average difference in payments between two workers with the same attributes but that are in different labor markets,  $m = 1$  and  $m = 0$ . In order to do that, we use some techniques from the traditional literature on wage gap and some others from the treatment effects literature. Note however that in this paper it is not clear what should be called the “treatment group” and what should be called the “control group”, since we are not in fact comparing treatment and control groups in an experiment.

We arbitrarily fix that a worker is in the treatment group if he belongs to the distribution  $m = 1$ ; by analogy, a worker is said to be in the control group if he belongs to the distribution  $m = 0$ . This way we can interpret the controlled earnings differential estimations, which are comparisons between the earnings of the average individual in  $m = 1$  and his counterfactual earnings in  $m = 0$ , as a “treatment effect”.<sup>9</sup>

Assuming that there are only two possible labor markets,  $m = 0$  and  $m = 1$ , let us then define  $T_i$  as an indicator variable such that,  $T_i = \{ \text{individual } i \text{ is at sector } m = 1 \}$ . The worker  $i$ 's observed log-wage is then:<sup>10</sup>

$$(1) \quad w_i = (w_{i,1} - w_{i,0}) T_i + w_{i,0}.$$

Following Heckman (1990), we are interested in estimating the gain from moving an  $m = 1$  worker with a vector in  $\mathbf{R}^k$  of observable attributes  $\mathbf{x}_i$  from sector  $m = 0$  to  $m = 1$ . This is the *controlled earnings gap* specified in a broad sense. It can be seen below that it has the same mathematical expression of the so-called *average treatment effect on the treated*, which is:

$$(2) \quad \Delta = E_{\mathbf{x}}[\Delta(\mathbf{x})] = E_{\mathbf{x}}[E[w_1 | T = 1, \mathbf{x}] - E[w_0 | T = 1, \mathbf{x}]]$$

The main problem of estimating  $\Delta$  in (2) is that we can never observe  $E[w_0 | T=1, \mathbf{x}]$ . So, following the literature on treatment effects, we need a slightly weaker version of the traditional “unconfounded treatment assignment” given a set of covariates assumption (Rubin, 1977).<sup>11</sup> That is, we may assume that:

$$(3) \quad w_{i,1}, w_{i,0} \perp T_i | \mathbf{x}_i, \forall i,$$

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<sup>9</sup> “Treatment effect” might be a misleading term since it is not our goal to find any causal effect. However, we keep this terminology, mainly because most of the estimation procedures presented here are typical of the literature on the treatment effect.

<sup>10</sup> For a causal interpretation,  $w_{i,1}$  and  $w_{i,0}$  should be interpreted, following the treatment effect literature, as potential earnings of worker  $i$  in  $m = 1$  and  $m = 0$ , respectively.

<sup>11</sup> Again, as we are not interested in causal interpretations, uncorrelatedness is a sufficient assumption, being independence an unnecessary stronger assumption.

which implies:

$$(3a) \quad E[w_0|T = 1, \mathbf{x}] - E[w_0|T = 0, \mathbf{x}] = 0.$$

Equation (3) states that given  $\mathbf{x}_i$ , treatment is uncorrelated to earnings. This is a strong assumption that basically rules out any explanatory role of unobservable characteristics. With that assumption on, we might rewrite (2) as:

$$(4) \quad \begin{aligned} \Delta &= E_{\mathbf{x}}[E[w_1|T = 1, \mathbf{x}] - E[w_0|T = 1, \mathbf{x}]] = \\ &= E_{\mathbf{x}}[E[w_1|T = 1, \mathbf{x}] - E[w_0|T = 0, \mathbf{x}]] + \\ &+ E_{\mathbf{x}}[E[w_0|T = 0, \mathbf{x}] - E[w_0|T = 1, \mathbf{x}]] = \end{aligned}$$

$$(4a) \quad \Delta = E_{\mathbf{x}}[E[w_1|T = 1, \mathbf{x}] - E[w_0|T=0, \mathbf{x}]]$$

Thus, if we have discrete observable characteristics  $\mathbf{x}$ ,  $\Delta$  turns out to be:

$$(4b) \quad \Delta = \sum_{j=1}^{J_1 \dots J_k} f(x_{1,j}, \dots, x_{k,j}) \{E[w_1|T = 1, \mathbf{x}_j] - E[w_0|T = 0, \mathbf{x}_j]\},$$

where  $f(\cdot)$  is the probability mass function of  $\mathbf{x}$ , a random vector that can be decomposed into  $J_1 \dots J_k$  categories. However, if  $\mathbf{x}$  is continuously distributed with distribution function  $F(\cdot)$ :

$$(4c) \quad \Delta = \int \{E[w_1|T = 1, \mathbf{x}] - E[w_0|T = 0, \mathbf{x}]\} dF(\mathbf{x}),$$

Notice that it can be hard to estimate  $\Delta(\mathbf{x})$  for every  $\mathbf{x}$ , mainly because  $\mathbf{x}$  is multidimensional and might be continuously distributed. Thus, in order to estimate  $\Delta$  we need some device that allows us to overcome such multidimensionality problem. Following Rosenbaum and Rubin (1983), we define the propensity-score (p-score) as the probability of being in  $m = 1$  given a set of vector of covariates  $\mathbf{x}$ .<sup>12</sup> Write the propensity-score as being:

$$(5) \quad p(\mathbf{x}_i) = \Pr[T_i = 1 | \mathbf{x}_i]$$

If we assume that  $0 < p(\mathbf{x}_i) < 1$  for all workers  $i$ , it can be shown that equation (3) implies:

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<sup>12</sup> We are assuming there are just two possibilities for a worker: either labor market  $m = 1$  or  $m = 0$ .

$$(6) \quad w_{i,1}, w_{i,0} \perp T_i \mid p(\mathbf{x}_i), \forall i$$

Equation (6) reduces the problem of dimensionality to a single univariate scale, the range of  $p(\mathbf{x})$ . Now, note that if we know  $p(\mathbf{x}_i)$ , we can proceed in an analogous way to the derivation of equation (4a), in order to re-express  $\Delta$  as:

$$(7) \quad \Delta = E_{\mathbf{x}}[E[w_1|T=1, p(\mathbf{x})] - E[w_0|T=0, p(\mathbf{x})]] =$$

$$(7a) \quad \Delta = E_{p(\mathbf{x})}[E[w_1|T=1, p(\mathbf{x})] - E[w_0|T=0, p(\mathbf{x})]] =$$

Now, let us try to reconcile this approach with the usual approach of using Mincer equations in the estimation of the controlled wage gap. A typical generalized Mincer equation is of the form:

$$(8) \quad w_{i,j} = h_j(\mathbf{x}_{i,j}) + u_j(\mathbf{z}_{i,j}), \quad i = 1, \dots, N \text{ and } j = 0, 1$$

where  $\mathbf{z}$  is a vector of non-observable characteristics and  $h(\cdot)$  and  $u(\cdot)$  are unknown real-valued functions. We also assume that for all  $i$ :

$$(9) \quad w_{i,j} = h_j(\mathbf{x}_{i,j}) + \varepsilon_{i,j}; \text{ and } E[w_j|\mathbf{x}_j] = h_j(\mathbf{x}_j), j = 0, 1$$

*i.e.*, that the unobservable and observable characteristics are not correlated.<sup>13</sup>

We can now, using (9), write the parameter of interest  $\Delta$  as:

$$(10) \quad \Delta = E_{\mathbf{x}}[\Delta(\mathbf{x})] = E_{\mathbf{x}}[E[h_1(\mathbf{x}_1) \mid T=1, \mathbf{x}] - E[h_0(\mathbf{x}_0) \mid T=1, \mathbf{x}]]$$

Equation (10) can be simplified once we assume a parametric and known form for  $h(\cdot)$ :

$$(11) \quad h_j(\mathbf{x}_{i,j}) = \alpha_j + \beta_j' \mathbf{x}_{i,j}, j = 0, 1,$$

and also assuming, as in Heckman (1990), the following simplifying assumption (12), which allows us to estimate wage differentials without the need to look for complicated sample selection-correction models:

$$(12) \quad E[\varepsilon_1 - \varepsilon_0 \mid T=1, \mathbf{x}] = 0, \text{ yielding:}$$

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<sup>13</sup> Henceforth, we will sometimes refer to the observable and to the unobservable characteristics respectively as the “observables” and the “unobservables”.

$$(13) \quad \begin{aligned} \Delta &= \alpha_1 - \alpha_0 + \beta_1' E[\mathbf{x}_1 | T = 1] - \beta_0' E[\mathbf{x}_0 | T = 1] = \\ &= \alpha_1 - \alpha_0 + (\beta_1 - \beta_0)' E[\mathbf{x}_1 | T = 1] + \beta_0' (E[\mathbf{x}_1 | T = 1] - E[\mathbf{x}_0 | T = 1]). \end{aligned}$$

Now, if  $\mathbf{x}_1$  and  $\mathbf{x}_0$  are identically distributed, then the “composition effect” is zero, that is:

$$(14) \quad \beta_0' (E[\mathbf{x}_1 | T = 1] - E[\mathbf{x}_0 | T = 1]) = 0.$$

Finally:

$$(15) \quad \Delta = \alpha_1 - \alpha_0 + (\beta_1 - \beta_0)' E[\mathbf{x} | T = 1].$$

If we rely on an even stronger assumption on the functional forms of  $h_1(\cdot)$  and  $h_0(\cdot)$ , that is, if  $\beta_1 = \beta_0$ , then:

$$(16) \quad \Delta = \alpha_1 - \alpha_0$$

## IV.2 Estimation

Several approaches for estimation of  $\Delta$  were proposed in the literature. We shall present some of them, divided into three major classes: non-parametric, semi-parametric, and parametric estimators.

### IV.2.1 Non-parametric approach

The following estimator does not need any assumption on the functional form of  $w$  for its consistency to  $\Delta$ . Because of that characteristic, we call it a non-parametric estimator.<sup>14</sup> In fact, it is a special case of a larger class of matching estimators, as described in Heckman, Ichimura and Todd (1998).

For the case of discrete covariates, the following equation describes such estimator:

$$(17) \quad \hat{\Delta}_{np} = \sum_{j=1}^{J_1 \dots J_k} \left\{ \frac{\sum_{i \in j} T_i}{\sum_{k=1}^J \sum_{i \in k} T_i} \left[ \frac{\sum_{i \in j} T_i w_i}{\sum_{i \in j} T_i} - \frac{\sum_{i \in j} (1 - T_i) w_i}{\sum_{i \in j} (1 - T_i)} \right] \right\}$$

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<sup>14</sup> Another way of making assumptions on the form of the earnings function is to estimate  $E[w|\mathbf{x}]$  non-parametrically, as proposed by Hahn (1998).

where the subscript  $np$  stands for non-parametric and. Notice that for such estimator to be consistent for  $\Delta$  it suffices that the “unconfoundness assumption” (equation (3)) holds.

## IV.2.2 Semi-parametric approaches<sup>15</sup>

In many situations a multidimensional vector of continuous covariates might force the use of the propensity score as described earlier. The main assumption needed for consistency of estimators based on the p-score is equation (6).

For estimators based on the p-score, a first and parametric estimation step is often made necessary: the estimation of the p-score. A traditional way of estimating the propensity score is by logistic regressions as in the equation below:

$$(18) \quad \Pr[T_i=1 | \mathbf{x}_i] = \exp(\gamma + \delta \cdot \lambda(\mathbf{x}_i)) / [1 + \exp(\gamma + \delta \cdot \lambda(\mathbf{x}_i))], \quad i = 1, \dots, N$$

where  $\lambda(\cdot)$  is a polynomial function to be chosen.

The fitted values of this estimation by maximum likelihood yield the estimated propensity score,  $\hat{p}(\mathbf{x}_i)$ .

### IV.2.2.1 Stratifying using the Propensity Score

Now assume that our specification for the logit is enough to fully condition on the observables that make up the assignment mechanism. If that condition is satisfied then, following Rosenbaum and Rubin (1984), who proposed using a discrete distribution of the p-score to estimate equation (7a). For that to be a feasible procedure, they use  $\hat{p}(\mathbf{x})$  instead of  $p(\mathbf{x})$  to estimate  $\Delta$ . Rosenbaum and Rubin (1984) stratify the observations along quantiles of  $\hat{p}(\mathbf{x})$  and estimate the difference between treatment and control outcomes for each stratum. In order to check balance of covariates within each stratum, they perform F-tests to the difference in means of each covariate between treatment and control groups. They conclude that sub-classifying the sample accordingly to five quantiles of the estimated p-score yielded the desired balance.

After deciding how many strata (quantiles of  $\hat{p}(\mathbf{x})$ ) the sample will be divided into, one can estimate  $\Delta$  by:

$$(19) \quad \hat{\Delta}_{sps} = \sum_{q=1}^Q \left\{ \frac{\sum_{i \in q} T_i}{\sum_{k=1}^Q \sum_{i \in k} T_i} \left[ \frac{\sum_{i \in q} T_i w_i}{\sum_{i \in q} T_i} - \frac{\sum_{i \in q} (1-T_i) w_i}{\sum_{i \in q} (1-T_i)} \right] \right\}$$

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<sup>15</sup> We are using the term semi-parametric estimation in a slightly different way from that one, for instance, that Powell (1994) has defined. A probably better definition for the class of estimators in this section would be “semi-nonparametric” since we use a parametric first step in order to later on to estimate  $\Delta$  non-parametrically.

where the subscript *sps* stands for “stratified on p-score”,  $q$  is a quantile of  $\hat{p}(\mathbf{x})$  and  $Q$  is the number of quantiles that provide a good balance on the covariates.<sup>16</sup> In this paper we use the above-mentioned estimator stratifying each pair of distributions into 50 blocks. However, as we will see in the results, even such large number of data divisions is not able to provide a good balance for some pairs.

#### IV.2.2.2 Reweighting using the Propensity Score

The propensity-score approach can be used to estimate  $\Delta$  in several different ways. The previous way, stratifying on the p-score, can be seen as a special case of a matching estimator as defined by Heckman, Ichimura and Todd (1998), with weights coming from an approximate discrete distribution of  $p(\mathbf{x})$ . Note that although being a matching estimator in a general sense, it is not what the literature calls “matching on the p-score”, which is well described by Angrist and Krueger (1999) and Dehejia and Wahba (1999).

Another “matching estimator” in the broad sense is the so-called estimator based on “reweighing on the p-score”.

DiNardo, Fortin and Lemieux (1996) came up with a way to reweigh a distribution and find a counterfactual one. Their methodology to compare two distributions requires finding a third and counterfactual distribution that should be interpreted as the distribution that would have prevailed for individuals in the control group if their attributes had been the same as the treated ones but they had been paid accordingly to the wage structure of the control group. The weights  $\phi_i$  to be applied to every individual  $i$  in the control group in order to reach the new counterfactual distribution can be estimated by:

$$(20) \quad \hat{\phi}_i = \frac{\sum_{j=1}^N (1-T_j) \hat{p}(\mathbf{x}_i)}{\sum_{j=1}^N T_j [1 - \hat{p}(\mathbf{x}_i)]}.$$

With the same set of assumptions hold so far, Dehejia and Wahba (1999) showed that it is possible to consistently estimate  $\Delta$  by using the following estimator:

$$(21) \quad \hat{\Delta}_{rps} = \sum_{i=1}^N w_i \left( \frac{T_i}{\sum_{k=1}^N T_k} - \frac{\phi_i (1-T_i)}{\sum_{k=1}^N (1-T_k)} \right),$$

which can be interpreted as an average difference in means between the treatment and the counterfactual of the control group. In equation (21) the subscript *rps* stands for “reweighing on the p-score”.

This estimator presents as an advantage over the previous one that no discretionary actions should be taken to decide in how many pieces the sample should be divided. However, it still suffers from the same problem that any estimator based on p-score faces, which is the reliance on

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<sup>16</sup> Dehejia and Wahba (1999) develop an algorithm for the joint decision of the functional form of  $\lambda(\cdot)$  in equation (18) and the number of strata  $Q$ . In this paper, for simplification, we treated  $\lambda(\cdot)$  as being an identity mapping.

its parametric part, the specification of the functional form of  $\Pr[T=1 | \mathbf{x}]$ . Moreover, the “reweighing on the p-score” estimator faces another problem that is related to those observations whose estimated p-score is close enough to one to cause distortions in the estimation.

### IV.2.3 Parametric Approaches

In this part we consider two overwhelmingly used parametric estimators for the controlled earnings gap: Oaxaca-Blinder and pooling-regression coefficient estimators.<sup>17</sup>

#### IV.2.3.1 Oaxaca-Blinder Earnings Gap

If equations (9) – (15) hold, then the Oaxaca-Blinder approach for controlled earnings gap, which is estimated traditionally by OLS, is a consistent estimator for  $\Delta$ . The formula for the “Oaxaca-Blinder” earnings gap estimator is:

$$(22) \quad \hat{\Delta}_{ob} = \hat{\alpha}_1 - \hat{\alpha}_0 + (\hat{\beta}_1 - \hat{\beta}_0)' \frac{1}{N} \sum \mathbf{x}_{i,l},$$

where  $\hat{\alpha}_1$  and  $\hat{\beta}_1$ ; and  $\hat{\alpha}_0$  and  $\hat{\beta}_0$  are OLS coefficients of the regression of  $w_j$  on  $\mathbf{x}_j$  and an intercept for  $j = 0$  and 1.

#### IV.2.3.2 Pooling-regression coefficient

If, in addition to equations (9) – (15), equation (16) also holds, then we can estimate consistently  $\Delta$  in a simpler way. That is,

$$(23) \quad \hat{\Delta}_{pr} = \hat{\alpha}_1 - \hat{\alpha}_0$$

where *pr* stands for pooling regression. As the name indicates, this estimator is the OLS coefficient of  $T$  in a pooled regression of log-wages as dependent variable and  $T$ ,  $\mathbf{x}$  and a constant as regressors. The observations in such regression are the pool of  $m = 1$  and  $m = 0$  workers.

The main advantage of this estimator over the Oaxaca-Blinder estimator is its simplicity in estimation. However, consistency is achieved only after the more restrictive assumption,  $\beta_1 = \beta_0$ .

### IV.2.4. Comparing the several approaches

The non-parametric estimator is feasible in the specifics of this paper only because we have at most five covariates, all of them discrete. However, this is not always the case and many studies cannot rely on this approach for estimating the average treatment effect.

The alternatives are either parametric or semi-parametric. As we have seen, parametric approaches look simpler, but at the expenses of requiring additional assumptions on the functional

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<sup>17</sup> The Oaxaca-Blinder estimator for the controlled wage gap appeared firstly in Oaxaca (1973) and Blinder (1973).

form of the log-earnings function. Semi-parametric approaches might look better at a first glance, but they also suffer from problems in the functional form specification of the probability of being treated given observable attributes. And moreover sometimes one needs to take some discretionary decisions or faces problems with the predicted values of the p-score that might reflect on the estimation of the average treatment effect.

## **V. Estimation results**

### **V.1 Log-earnings regressions results**

The parametric approach depends on the estimates of Mincer equations for the six log-earnings distributions available (Rede, PNAD Private, and PNAD Public, for 1995 and 1997). Table 3 presents the results of these estimations.

### **V.2 Average Treatment Effects and Counterfactual Distributions**

Table 4 presents the estimates of the average treatment effect (ATE) when comparing the 4 pairs of earnings distributions, which constitute the 4 intermediate steps proposed in Case 1 at the end of Section III for decomposing the total wage gap. We estimate the ATE, controlling for observable characteristics, by using the parametric, semi-parametric and non-parametric methods discussed in the previous Section. In particular, we also show how the results for the nonparametric approach vary as we add more controls. The idea is to test how robust are the results with respect to the choice of matching techniques. The ATE gives the difference between the average actual earnings of the treatment group and the one that would prevail if the characteristics of the treatment group were evaluated at the prices of the control group.

The first column of the Table presents the results for the first step of the decomposition, which is the most important for the objective of this paper. The first column compares the two distributions of private sector workers in 1997: the former Rede workers (the treatment group) and PNAD workers (the control group). The question being posed is: what would be the earnings of a Rede worker if his characteristics were valued as a typical PNAD private sector worker?

The result is a negative and large ATE, which is very robust with respect to the method used. The estimates vary in the range  $[-0.398, -0.324]$ . The most flexible method, the nonparametric approach, controlling for age, schooling, region, sector and occupation, gives an estimate of  $-0.365$ . That is, according to this estimate, the average log-earnings of a former Rede worker would be 0.365 higher than his actual log-earnings, if his characteristics were evaluated as in the private sector as a whole. This corresponds to average actual earnings 30.6% lower than the average of the counterfactual distribution. These former Rede workers, not only suffered a decrease in their actual earnings with respect to what they were receiving at Rede, but also observed a considerable decrease with respect to their best estimate of what they would make in the private sector, given their observable characteristics.

The second column of Table 4 presents the results for the second pair of distributions, the ATE of being in the private sector (treatment group) in 1997 when using the public sector in the same year as a control group. The ATE is also very robust to the choice of methods, varying from 0.027 to 0.086. The nonparametric method, when using all available controls, gives an estimate of 0.044. This means that the private sector is paying on average 4.5% more than the public sector when one controls for observable characteristics.

The third column of Table 4 shows a slight decrease of public sector wages between 1995 and 1997. The ATE of 1997 is  $-0.016$  according to the nonparametric method, when controlling for age, schooling, region and occupation. The fourth column of the Table suggests that Rede workers

were better paid in 1995, on average, than equally qualified workers in the public sector as a whole – as measured by their observable characteristics. The estimates range from  $-0.113$  to  $-0.064$ , the estimate given by the nonparametric approach when using controls for age, schooling and region.

Comment box-plots (Figures 3a to 3d).

Figures 4a to 4d extend the analysis to the comparison of the complete distributions for each of the 4 pairs discussed above. Each graph displays the actual distribution of the treatment group (thick and black line), the control group (dotted and blue line), and the counterfactual distribution (thin and red line). As above, the counterfactual distribution gives the prices of the control group to the characteristics of the treatment group.

Figure 4a shows that the counterfactual distribution of evaluating Rede workers characteristics at the prices of the private sector is almost entirely to the right of the actual earnings distribution of these workers in the private sector. According to the counterfactual distribution, there would be a much smaller proportion of workers receiving less than 2 minimum wages and much more receiving higher wages.

Figure 4b, on the other hand, shows that the counterfactual distribution of evaluating private sector workers characteristics at the prices of the public sector in 1997 is almost entirely to the left of the actual earnings distribution of private sector workers.

Figure 4d shows how different are the counterfactual distribution of evaluating public sector workers characteristics at the prices paid at Rede in 1995 and the actual distribution of public sector workers. The counterfactual distribution is much more compact, tracking very closely the actual Rede earnings distribution. In fact, this Figure illustrates that the data set does not have enough variation in the covariates to simulate the differences from workers at Rede and the public sector as a whole.

### **V.3 The Treatment Effect by Human Capital**

The main result of the previous Section was that the whole distribution of earnings of former Rede workers is at the left of what would be expected given their characteristics, the counterfactual distribution. In order to help interpreting this result, this sub-section attempts to identify a pattern of treatment effects by some observable characteristics. In particular, we measure the treatment effect by a human capital index, which can be constructed at the individual level as discussed in Section IV.2. The question being posed is: who lost more from what was expected, those with high or low human capital.

Figures 5a to 5d plot the treatment effects for the 4 pairs of distributions against the human capital index. Figure 5a shows that the treatment effect of being a former Rede worker affected negatively all workers. However, the effect was larger (in absolute value) for those with high human capital than for those with low human capital.

Standard human capital theory can lead us to interpret this result in either an optimistic or a pessimistic way. The optimistic view is that those with high general human capital tend to invest more in specific human capital. Since this investment takes time to generate returns, we are observing these workers at the investment period and we should expect their earnings to increase in the future. Pessimists could argue that the value of general human capital has depreciated after so much time in a public firm, and that we could be observing permanent reductions in their earnings, without any tendency to a future increase. Pessimists could also argue that a possible public sector stigma effect could be higher for those with high human capital.

Figure 5b, on the other hand, shows that the treatment effect of being in the private sector when compared to the public sector declines with the level of human capital. Those with high

human capital have a negative treatment effect. That is, the private sector is paying them less than the public sector when controlling for observable characteristics. This is somewhat surprising, since one would expect that the public sector in Brazil remunerate better than the private sector the observable characteristics of those with low human capital, and not the opposite.

Finally, Figure 5d shows a huge dispersion of treatment effects of being a former Rede worker against being in the public sector as a whole, as already suggested by Figure 4d. Treatment effects increase substantially with the level of human capital.

The advantage of the human capital index is its continuity. The disadvantage is the difficulty to disentangle the effects of age and schooling. In order to separately analyze the effects of education, Figures 6a to 6d use the discrete levels of schooling as the human capital variable. One can basically observe the same patterns as in Figures 5a-5d, which corroborates the interpretations attributing a major role to schooling variables in the human capital index.

## V. Concluding remarks

[To be written]

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**Table 1: Summary statistics (Rede & PNAD)**

	Rede		PNAD			
	1995	1997	1995		1997	
	Public Sector	Private Sector	Public Sector	Private Sector	Public Sector	Private Sector
<b>Real Earnings (Sept./99R\$)</b>	971.51	835.46	1173.26	818.71	1140.19	814.86
<b>Log-earnings</b>	6.74	6.25	6.63	6.22	6.62	6.22
<b>Age</b>		40.58	39.84	38.83	39.48	38.87
<b>Years of schooling</b>						
0-3		5.1%	12.7%	23.3%	11.8%	21.9%
4		8.9%	12.9%	22.3%	8.8%	19.5%
5-7		15.5%	7.2%	14.4%	7.0%	15.7%
8		16.3%	8.9%	11.6%	7.8%	12.2%
9-10		10.5%	4.2%	4.2%	4.3%	4.4%
11		23.4%	23.6%	14.1%	27.0%	15.6%
12-14		4.9%	7.8%	2.7%	8.5%	2.8%
15		11.2%	13.4%	4.3%	13.1%	4.3%
16 or +		4.3%	9.5%	3.1%	11.7%	3.5%
<b>Region</b>						
Northeast		15.0%	24.5%	19.3%	21.7%	19.6%
South		18.5%	19.8%	17.9%	20.1%	18.1%
Southeast/Middle West		66.5%	55.7%	62.8%	58.3%	62.2%
<b>Sector of activities</b>						
Industry		12.3%	36.8%	40.6%	32.4%	39.8%
Wholesale		29.9%	1.4%	19.4%	1.2%	19.3%
Transp/Comunic		11.9%	20.5%	9.7%	19.2%	10.0%
Services		39.2%	24.3%	27.5%	31.3%	28.3%
Others		6.7%	17.0%	2.8%	15.9%	2.5%
<b>Occupational function</b>						
Formal		27.6%	90.5%	47.2%	85.5%	45.8%
Informal		12.6%	9.6%	13.0%	14.5%	14.2%
Self-employed		37.2%		31.1%		31.3%
Employer		22.7%		8.6%		8.8%
# of observations		1,186	1,483	32,831	1,350	34,344

**Table 2: Total Wage Gap**

	<sup>a</sup> Private x Public (Rede)	Rede x PNAD (Private, 1997)	Private x Public (PNAD, 1997)	1997 x 1995 (PNAD,Public)	PNAD x REDE (Public, 1995)
Total Wage Gap	-0.488	0.036	-0.401	-0.011	-0.112

note:

<sup>a</sup> - treatment x control

Table 3: Log-Earnings regression results

	Rede		PNAD						
	1995	1997	1995				1997		
	Public Sector	Private Sector	Public Sector	Public Sector	Private Sector	Private Sector	Public Sector	Private Sector	Private Sector
<b>Intercept</b>	6.123	5.917	1.451	1.983	3.758	4.085	2.850	3.912	4.228
<b>Age</b>	<b>0.005</b>	<b>-0.023</b>	0.184	0.163	0.091	0.079	0.122	0.083	0.072
<b>Squared Age(*10000)</b>	<b>2.512</b>	<b>3.424</b>	-19.399	-16.839	-9.357	-8.275	-12.029	-8.484	-7.465
<b>Years of schooling</b>									
4	<b>-0.108</b>	<b>0.229</b>	0.460	0.513	0.284	0.252	0.387	0.248	0.224
5-7	<b>-0.017</b>	<b>0.029</b>	0.720	0.781	0.417	0.373	0.585	0.384	0.346
8	<b>-0.028</b>	0.381	0.828	0.839	0.607	0.549	0.782	0.560	0.507
9-10	<b>0.026</b>	0.541	1.128	1.063	0.737	0.650	0.859	0.703	0.621
11	<b>-0.024</b>	0.683	1.306	1.237	1.001	0.901	1.269	0.962	0.862
12-14	<b>0.070</b>	0.659	1.570	1.503	1.383	1.233	1.523	1.364	1.225
15	<b>0.010</b>	1.186	1.913	1.855	1.778	1.594	1.744	1.654	1.494
16 or +	0.174	1.477	2.064	2.094	2.001	1.812	2.024	1.941	1.774
<b>Region</b>									
Northeast	<b>0.017</b>	-0.345	-0.274	-0.297	-0.466	-0.462	-0.399	-0.506	-0.488
South	<b>0.014</b>	<b>-0.046</b>	<b>0.006</b>	<b>-0.025</b>	-0.056	-0.075	<b>-0.019</b>	-0.063	-0.078
<b>Sector of activities</b>									
Wholesale		<b>-0.069</b>		<b>-0.074</b>	-0.024	-0.075	<b>0.069</b>	<b>-0.014</b>	-0.070
Transp/Comunic		0.317		-0.095	0.122	0.137	-0.104	0.176	0.192
Services		<b>0.114</b>		-0.427	-0.104	-0.117	-0.389	-0.051	-0.063
Others		<b>0.161</b>		0.256	<b>-0.020</b>	<b>0.015</b>	0.171	<b>-0.050</b>	<b>-0.016</b>
<b>Occupational function</b>									
Informal		<b>-0.055</b>				-0.256			-0.291
Self-employed		0.143				0.049			<b>0.005</b>
Employer		0.477				0.711			0.674
#obs	1186	1186	1483	1483	32831	32831	1350	34344	34344
R squared	0.108	0.266	0.4964	0.545	0.392	0.447	0.570	0.387	0.444

note: **bold** = not significant (5%)

**Table 4: Average Treatment Effect**

	<sup>a</sup> Rede x PNAD (Private, 1997)	Private x Public (PNAD, 1997)	1997 x 1995 (PNAD,Public)	PNAD x REDE (Public, 1995)
<b>Parametric Approaches</b>				
Oaxaca Decomposition $X_{t\beta t} - X_{t\beta c}$	-0.383	0.047	-0.041	-0.113
Dummy Coefficient	-0.380	0.043	-0.047	-0.019
<b>Non-Parametric Approach</b>	<b>-0.365</b>	<b>0.044</b>	<b>-0.016</b>	<b>-0.064</b>
<b>Non-Parametric Approach controlled by:</b>				
Age and schooling	-0.333	0.076	-0.060	-0.060
Age, schooling and region	-0.337	0.031	-0.067	<b>-0.064</b>
Age, schooling and sector	-0.324	0.086	-0.003	-
Age, schooling and occupation	-0.381	-	-	-
Age, schooling, region and sector	-0.335	<b>0.044</b>	<b>-0.016</b>	-
Age, schooling, region and occupation	-0.389	-	-	-
Age, schooling, sector and occupation	-0.369	-	-	-
Age, schooling, region, sector and occupation	<b>-0.365</b>	-	-	-
<b>Semi-Parametric Approach</b>				
Stratifying on P-score	-0.391	0.046	-0.054	-0.104
Reweighting using P-score	-0.398	0.061	-0.043	-0.107

note:

<sup>a</sup> - treatment x control

**Figure 1: Log-Earnings Density Function: REDE Employees: after and before leaving the public sector**

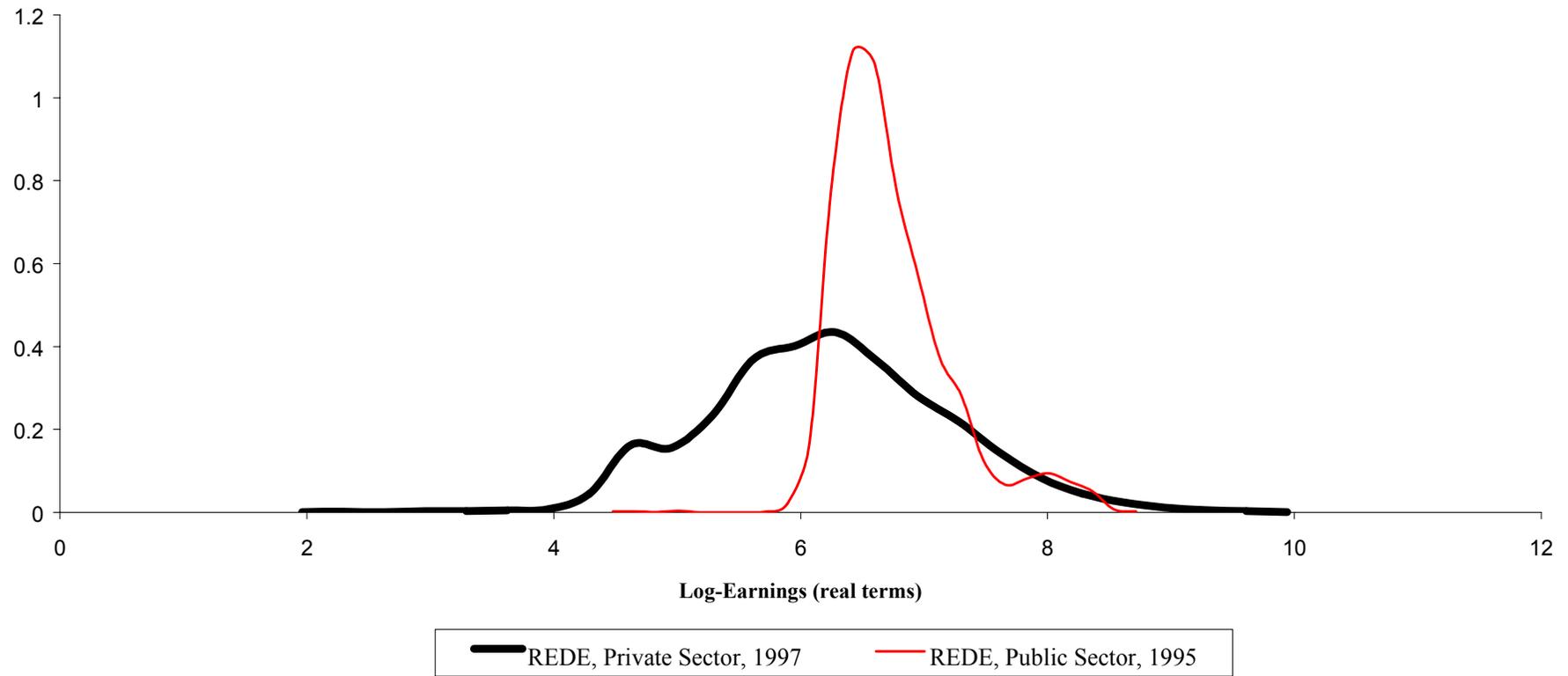


Figure 2a.

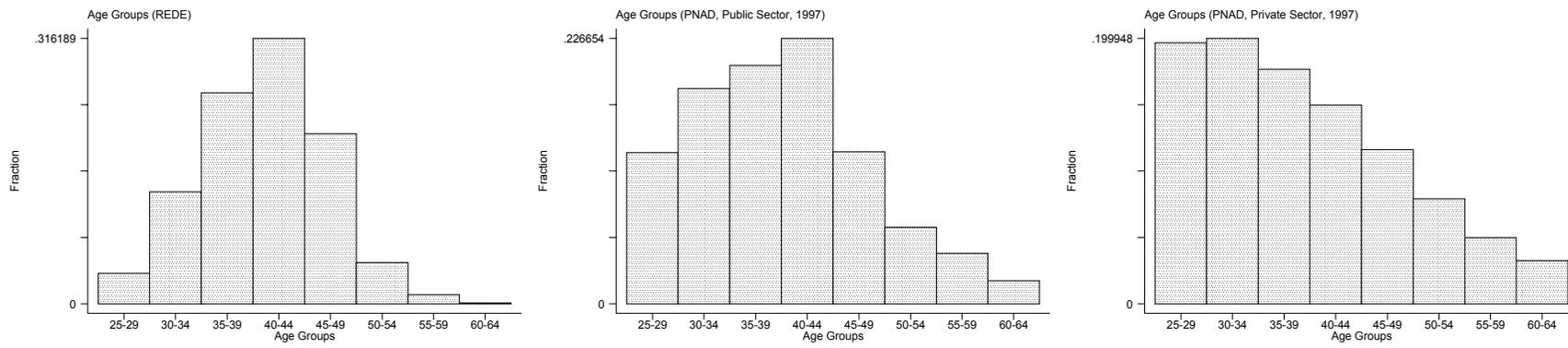


Figure 2b.

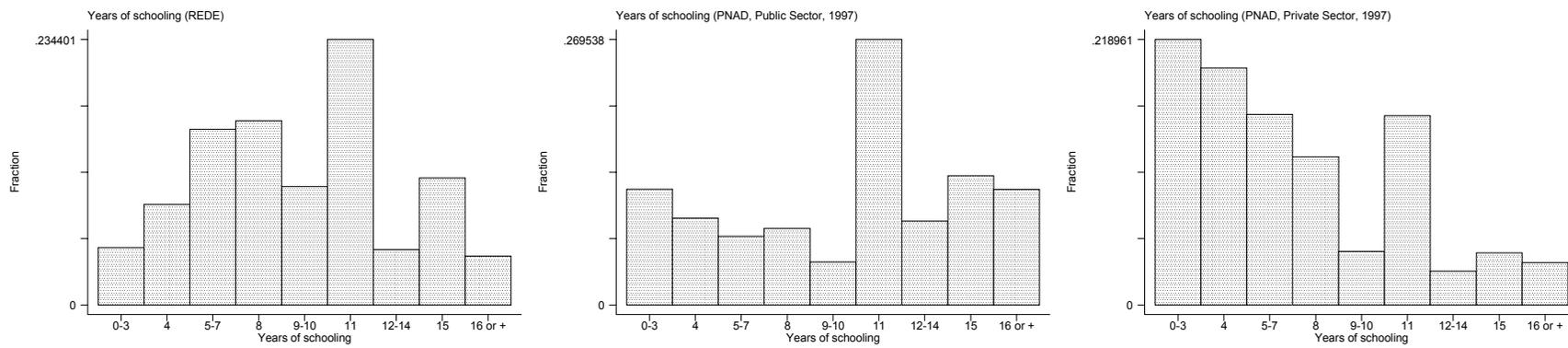


Figure 2c.

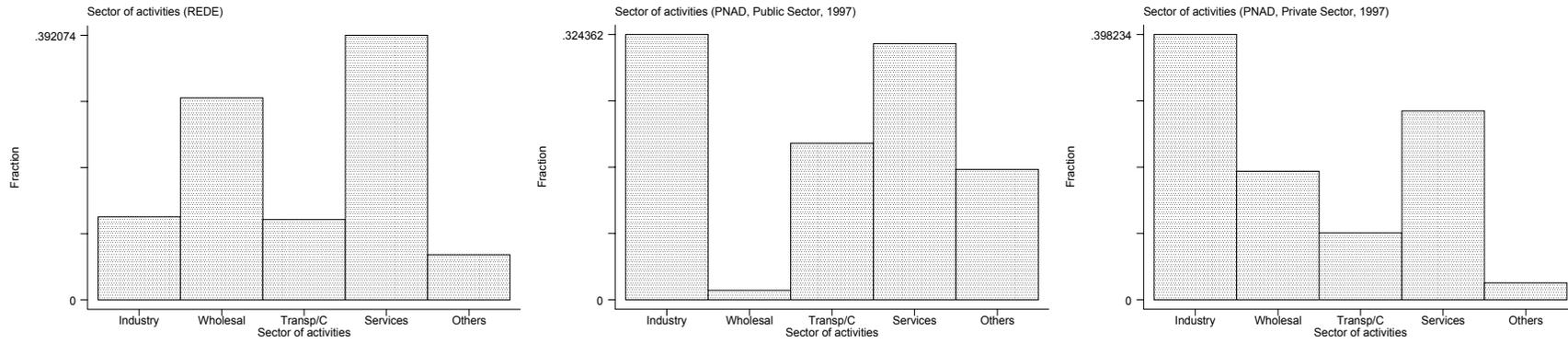


Figure 2d.

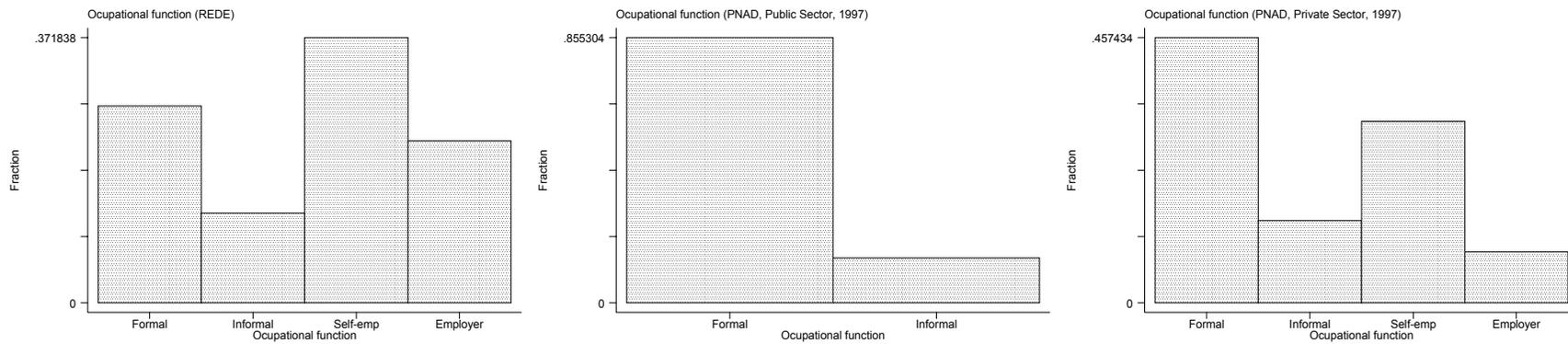


Figure 3a: P-Score of REDE (Private Sector, 1997)

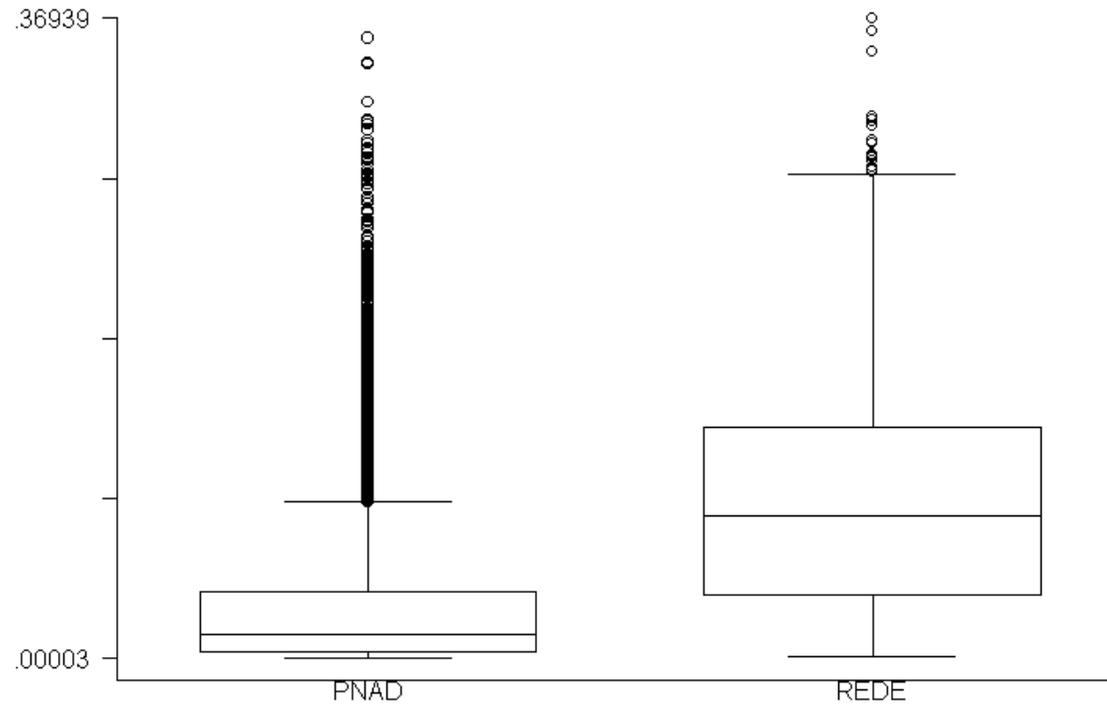


Figure 3b: P-Score of Private Sector (PNAD, 1997)

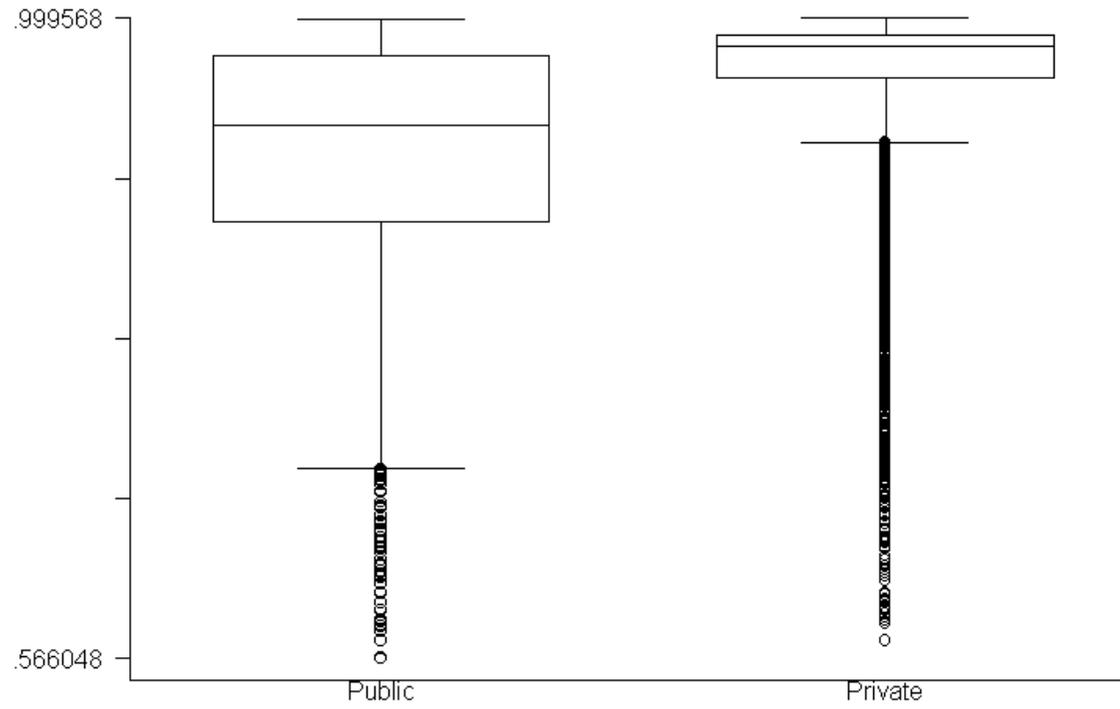


Figure 3c: P-Score of 1997 (PNAD, Public Sector)

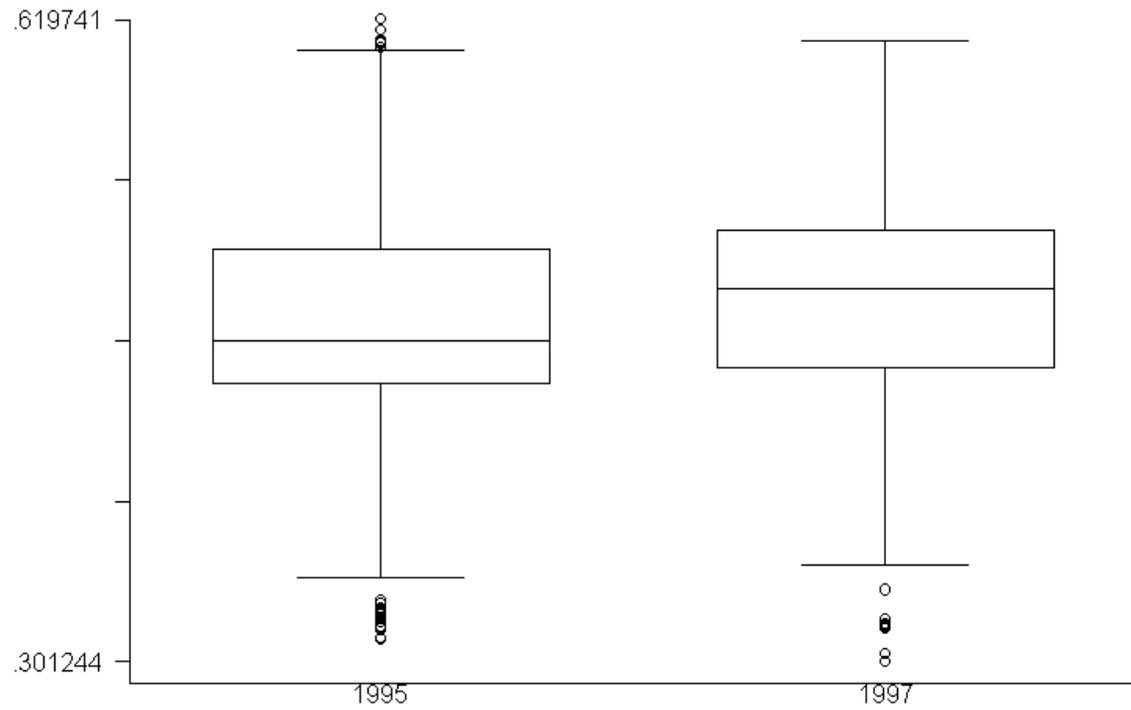
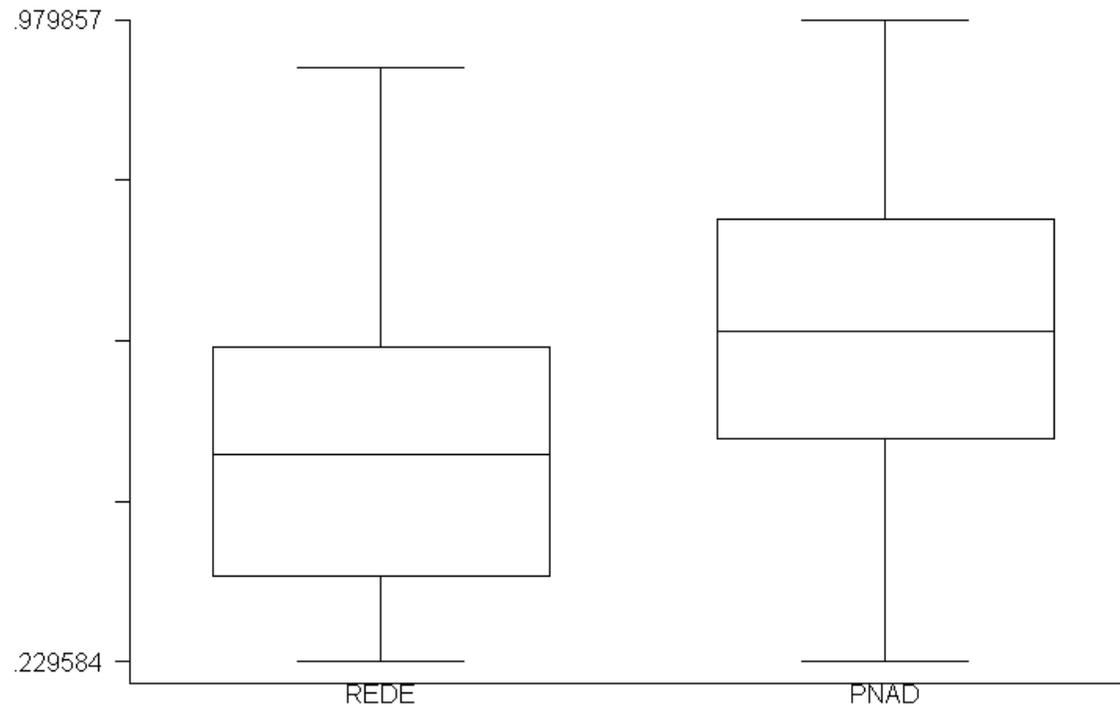
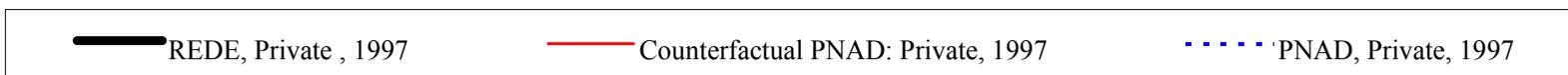
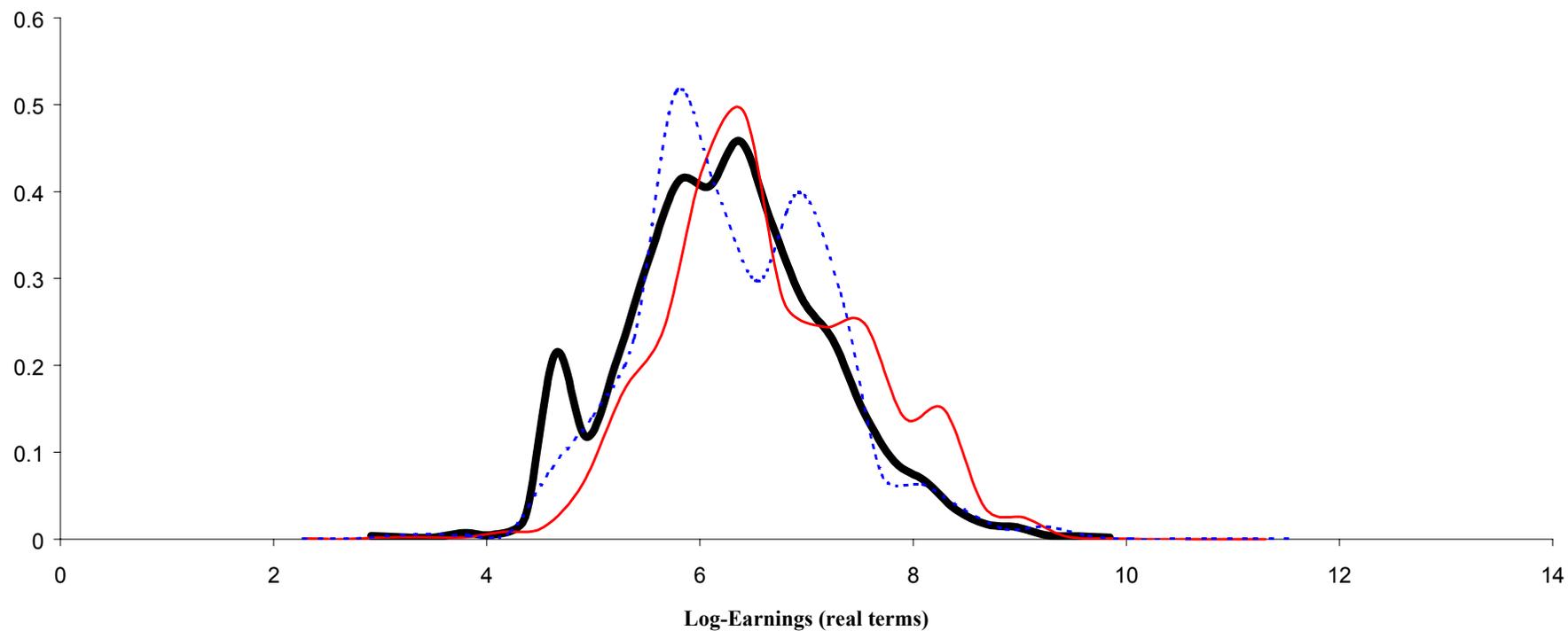


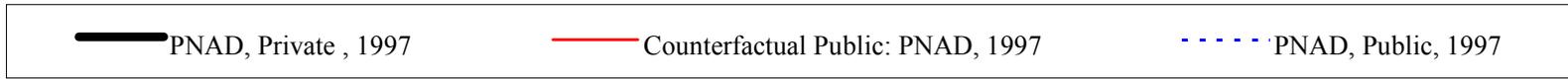
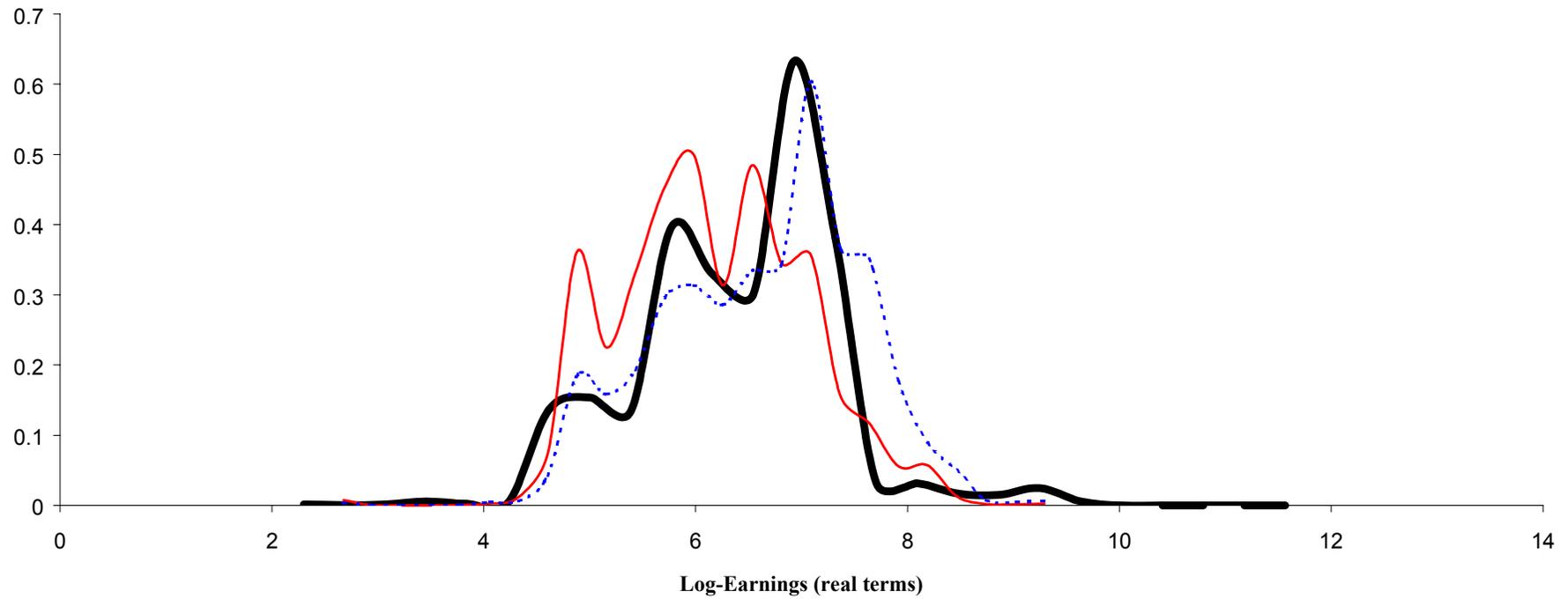
Figure 3d: P-Score of PNAD (Public Sector, 1995)



**Figure 4a: Log-Earnings Density Function: REDE X PNAD (Private Sector, 1997)**



**Figure 4b: Log-Earnings Density Function: Private X Public Sectors (PNAD, 1997)**



**Figure 4c: Log-Earnings Density Function: 1997 X 1995 (PNAD, Public Sector)**

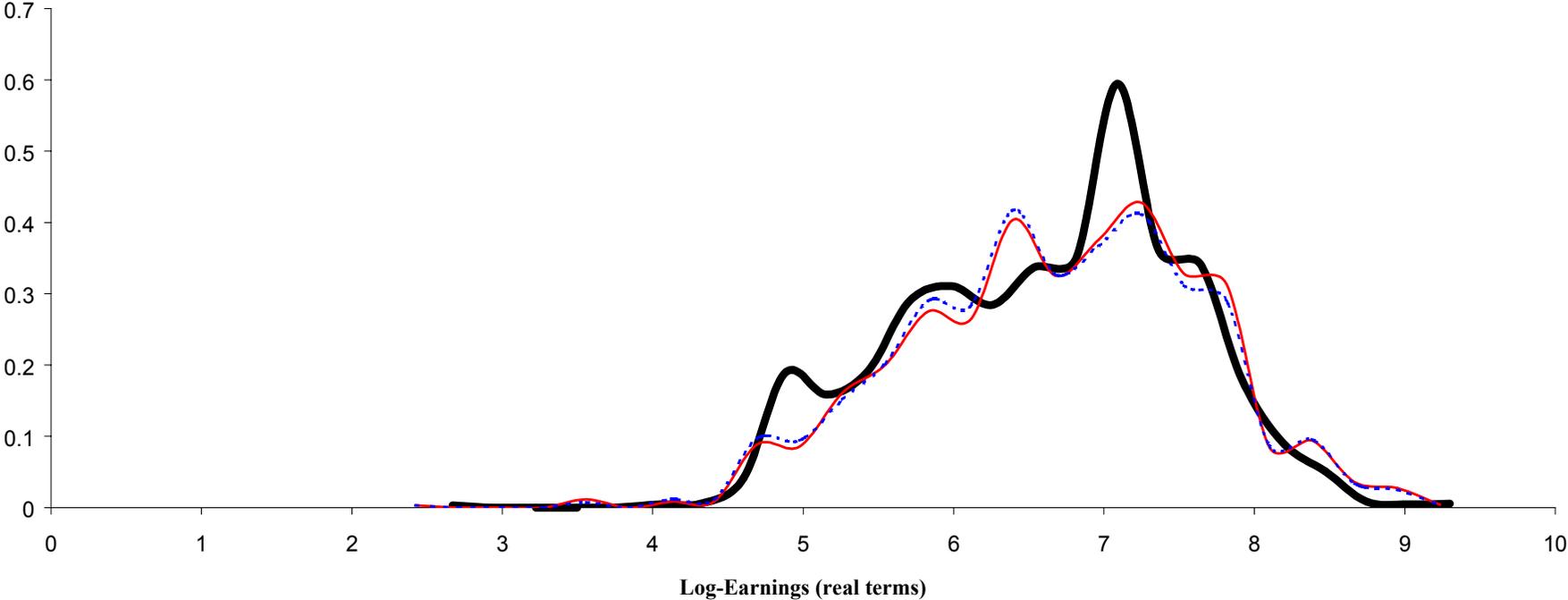


Figure 4d: Log-Earnings Density Function: PNAD X REDE (Public Sector, 1995)

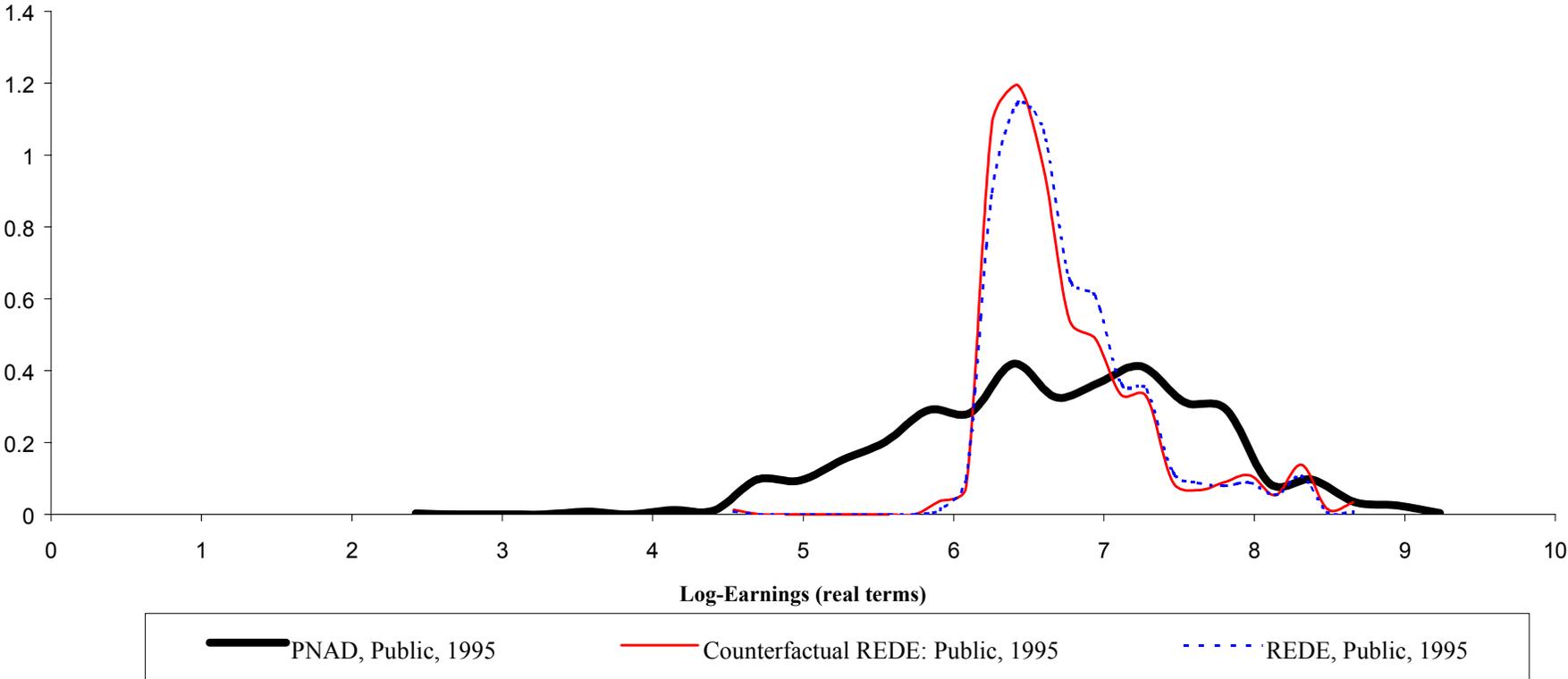


Figure 5a: Treatment Effect of REDE (Private Sector, 1997)

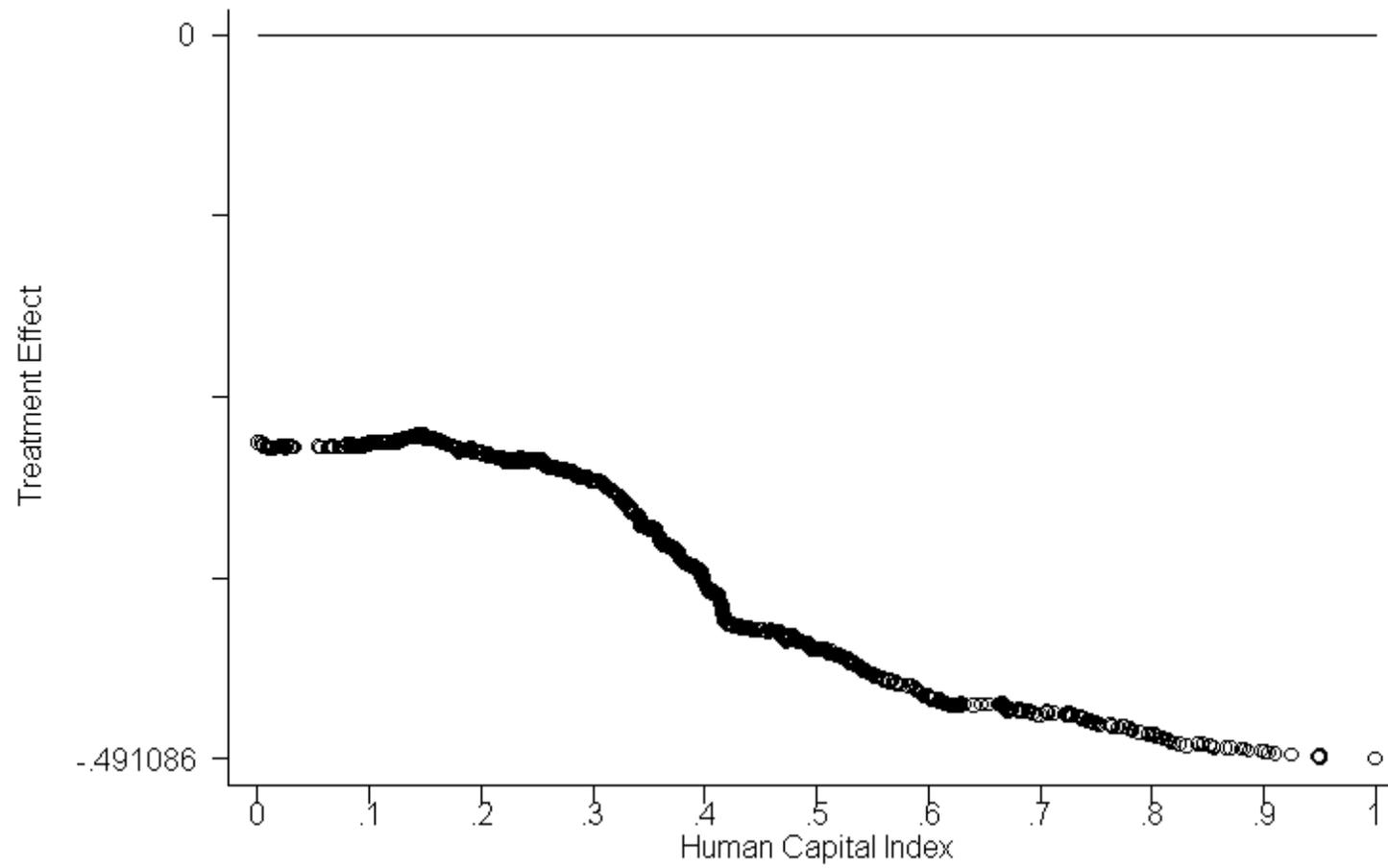


Figure 5b: Treatment Effect of Private Sector (PNAD, 1997)

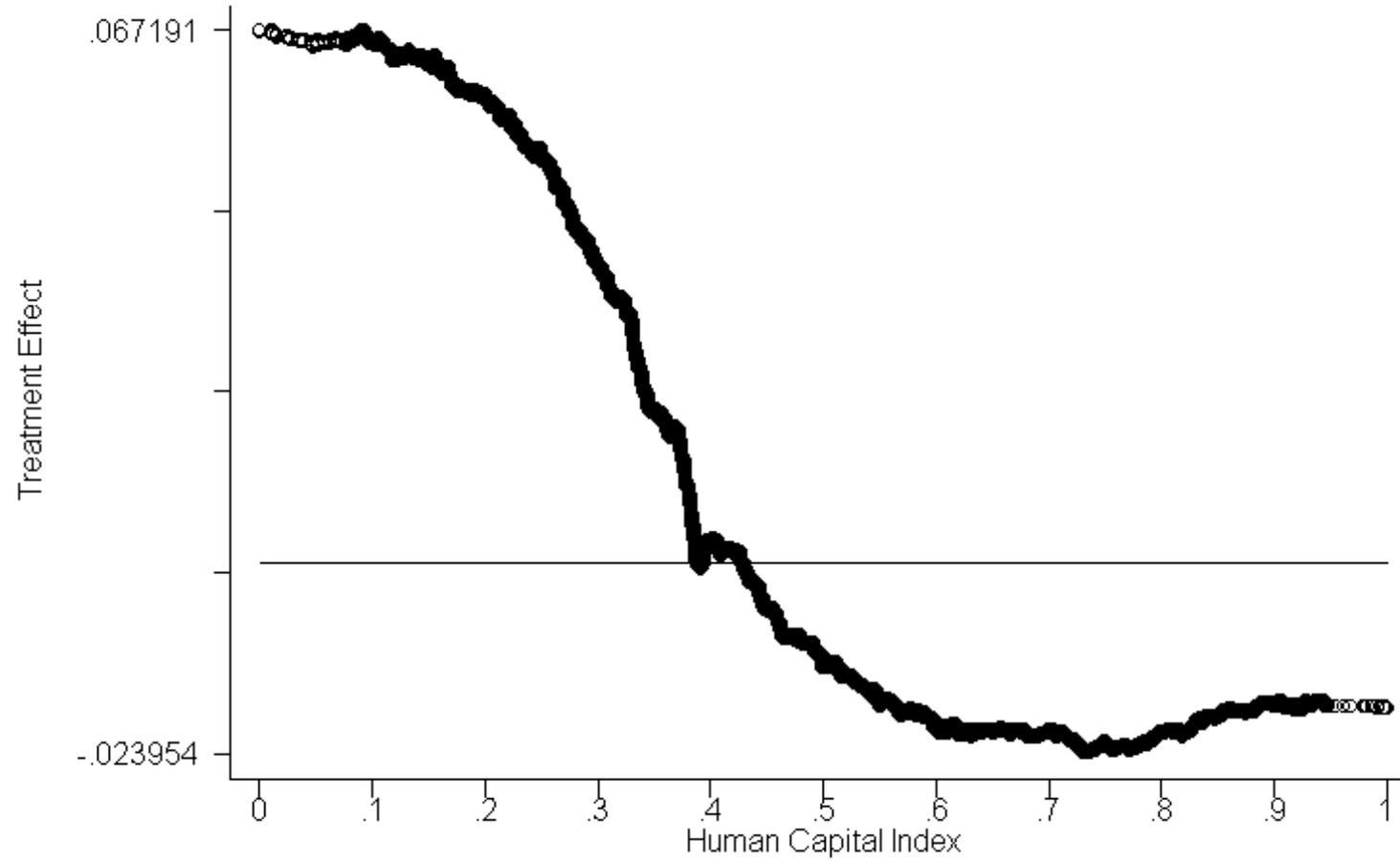


Figure 5c: Treatment Effect of 1997 (PNAD, Public Sector)

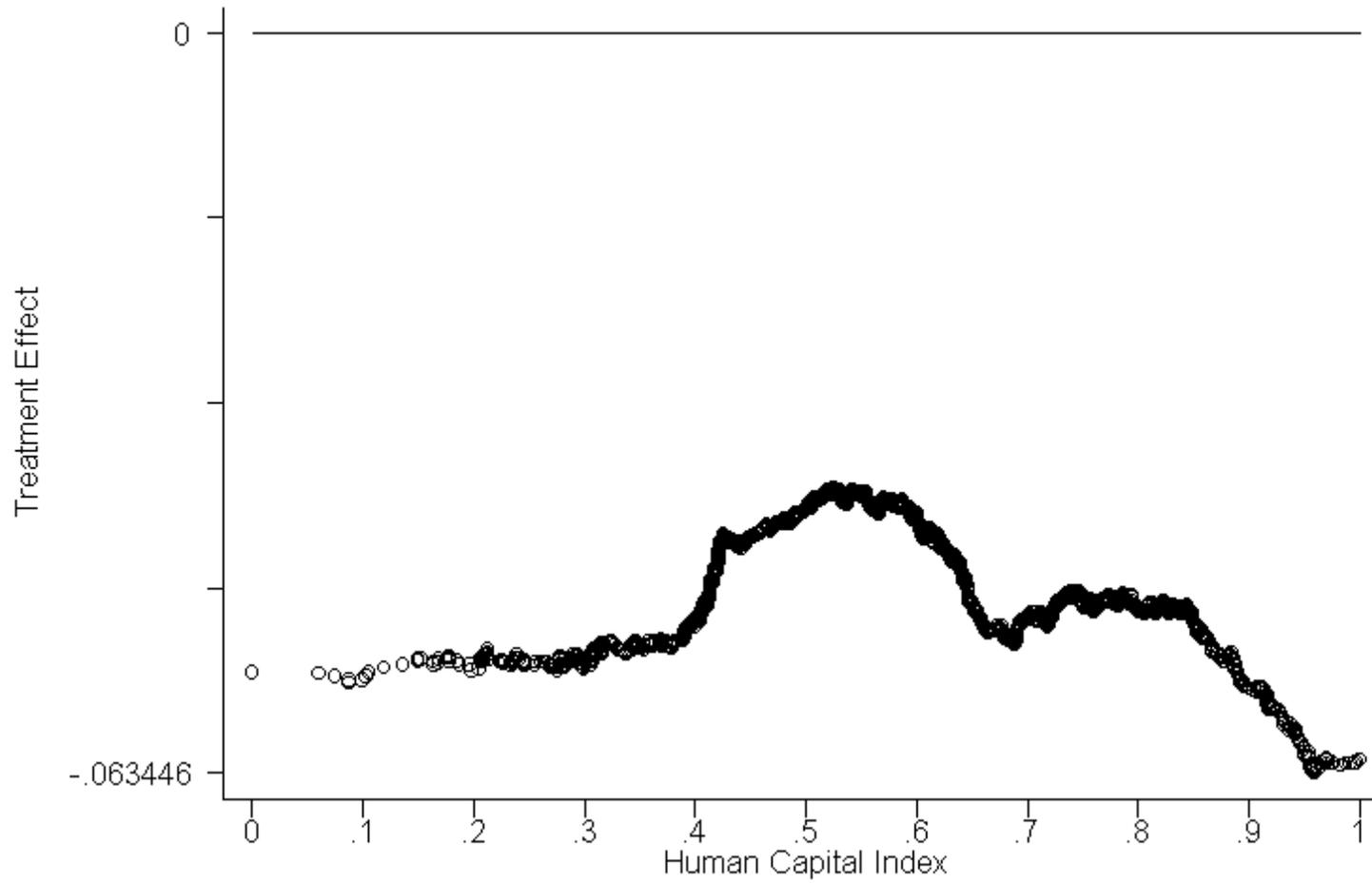


Figure 5d: Treatment Effect of PNAD (Public Sector, 1995)

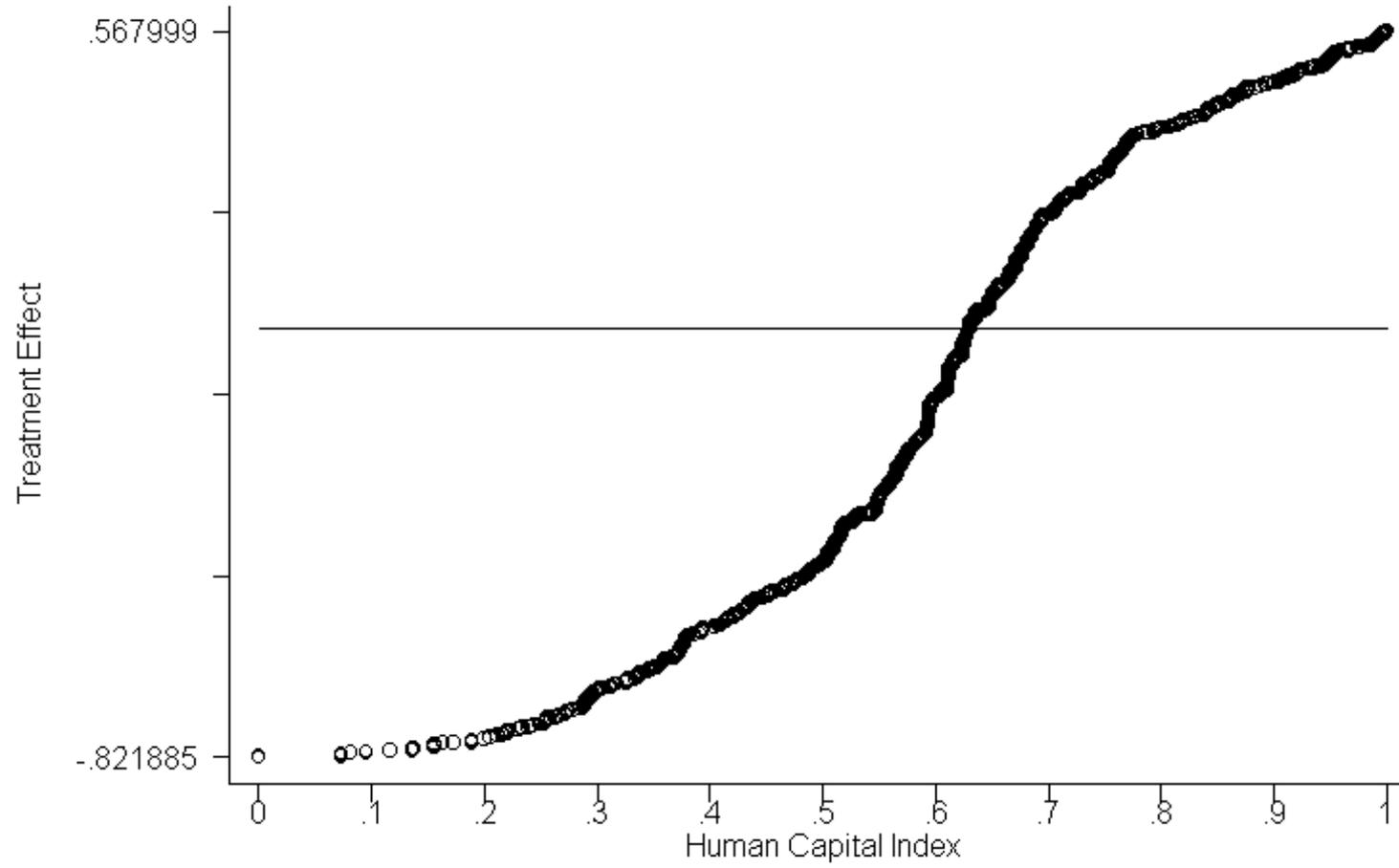


Figure 6a: Treatment Effect of REDE (Private Sector, 1997)

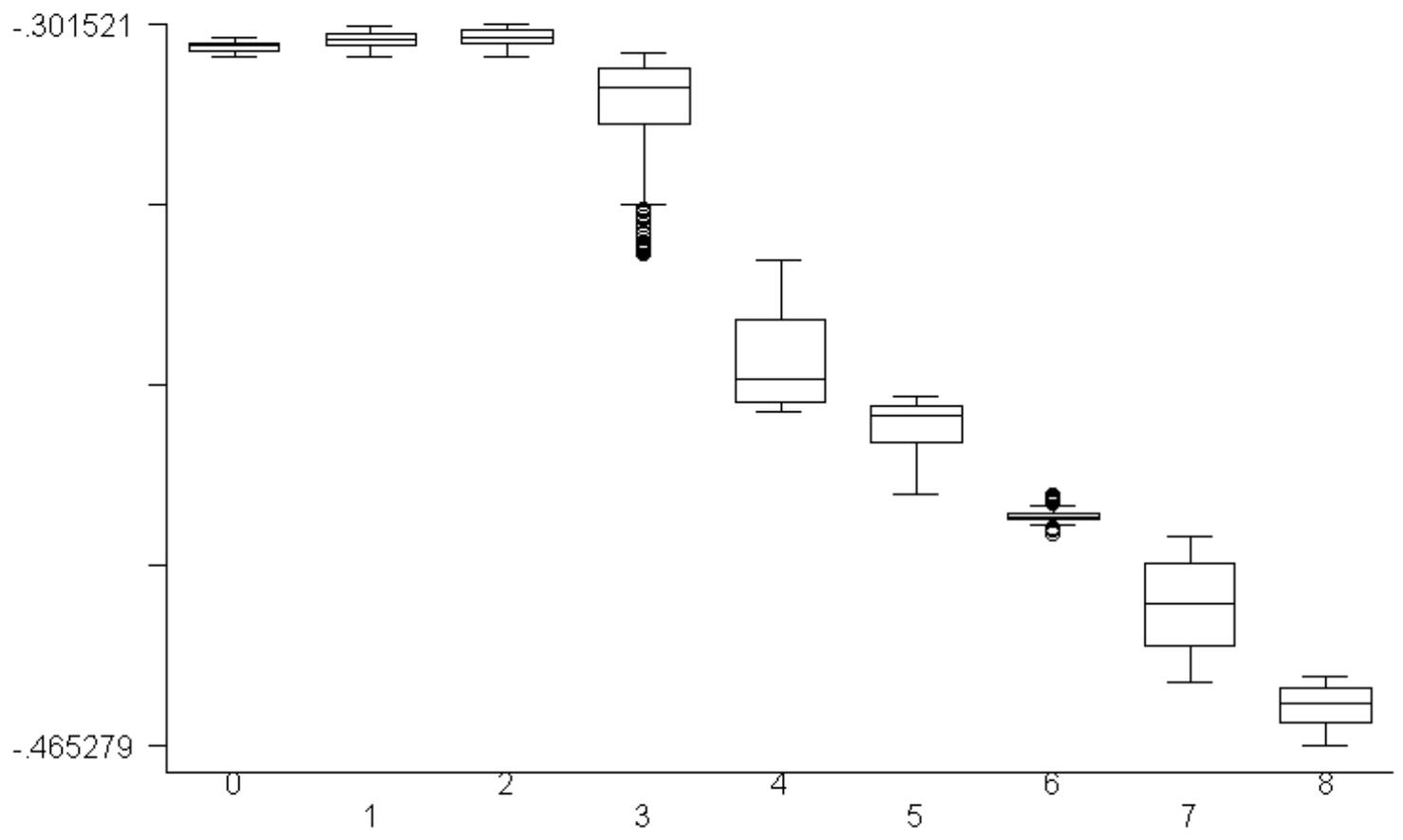


Figure 6b: Treatment Effect of Private Sector (PNAD, 1997)  
Treatment Effect

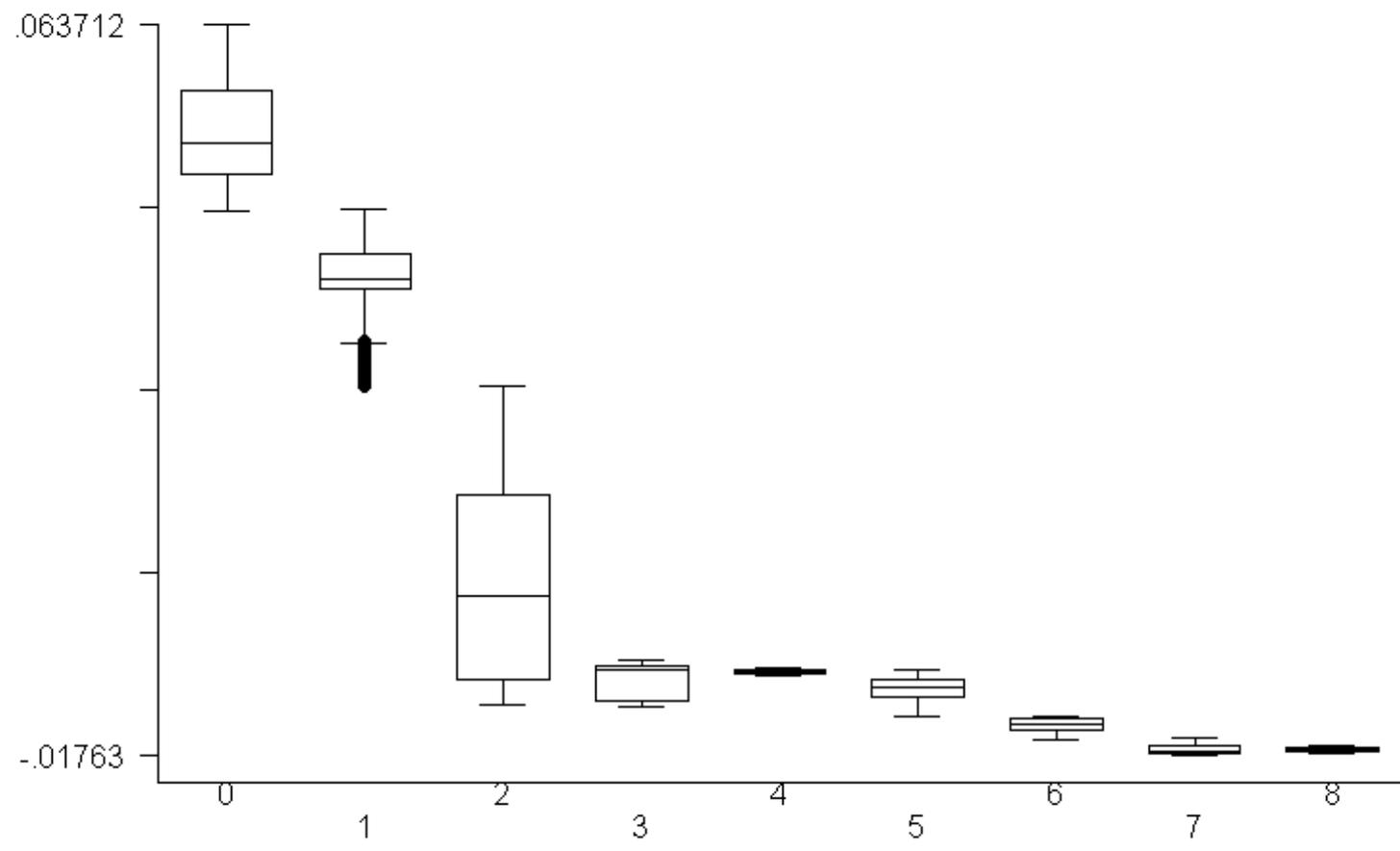


Figure 6c: Treatment Effect of 1997 (PNAD, Public Sector)  
☐ Treatment Effect

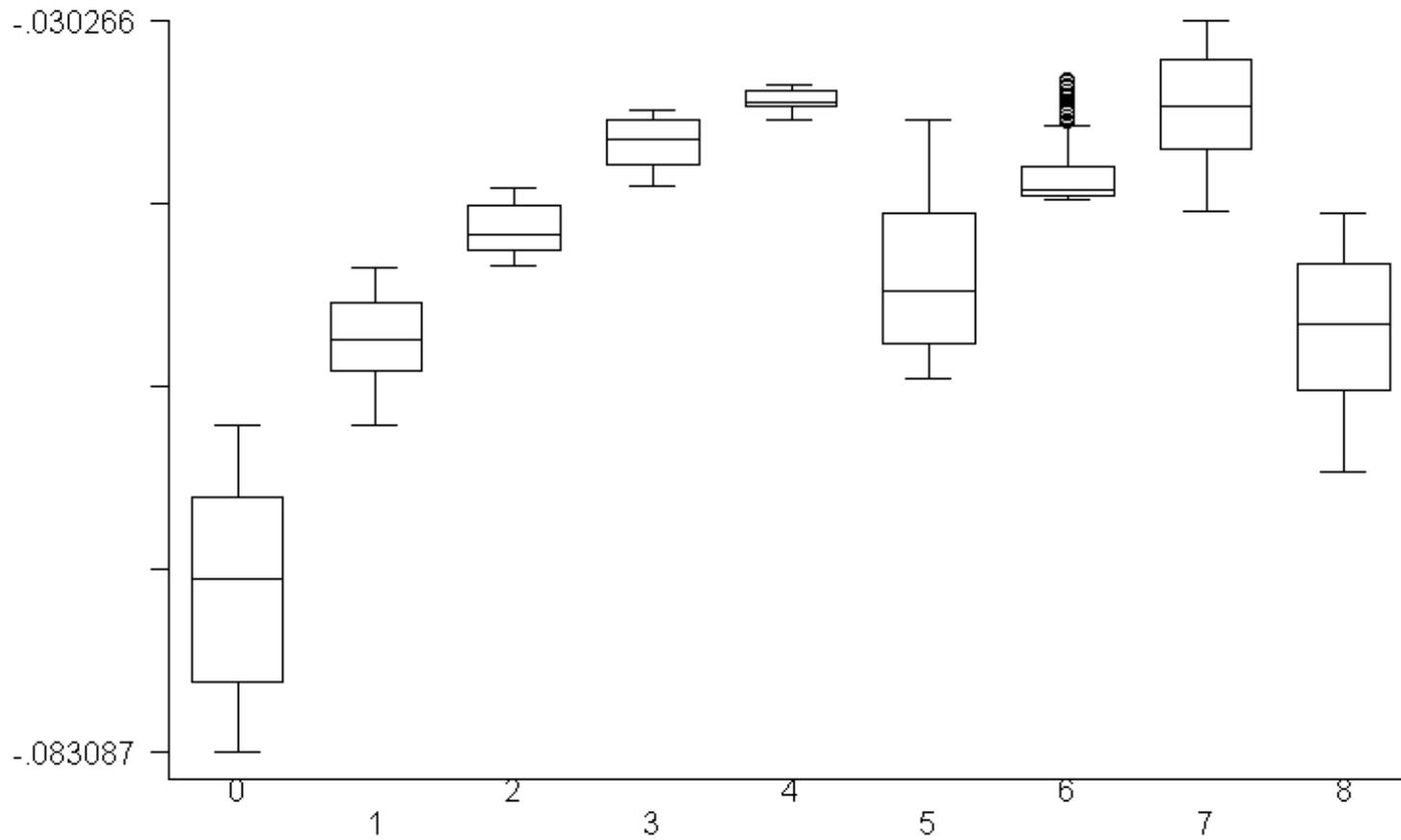


Figure 6d: Treatment Effect of PNAD (Public Sector, 1995)

