

# **Wage Differentials in South Africa's Labour Market: An analysis using micro-econometric techniques**

Aarifah Razak

Alain Kaninda

Dhevasha Chetty

Nicholas Kilimani

**2013**

## **Abstract**

*This report investigates the existence of wage differentials between part-time and full-time employees in South Africa. Considering that the sample used was obtained from a non-randomized observational study, the Oaxaca-Blinder Decomposition, the Nopo (2004) Matched Decomposition, Propensity Score Matching and Inverse Probability Weighting techniques were used to obtain estimates of wage differentials. The Oaxaca-Blinder results indicate an unexplained wage premium of R 49.25 to part-time employment which dominates the portion attributable to differences in observed endowments. The Nopo Matched Decomposition results indicate an hourly wage premium of R 47.22, with Endowment explaining 20.97% of the observed pay gap. Using Propensity Score Matching, an hourly wage premium to part-time workers of R47.22 was obtained before matching and R50.90 after matching is achieved. The IPW technique yields a wage premium to part-time workers of R47.9 when using the Average Treatment Effect (ATE) as the weight and R52.93 when the Average Treatment Effect on the Treated (ATT) is used.*

**JEL Code:** C12, J31

**Keywords:** Wage differential, Decomposition, ATT, ATE, Propensity Score Matching

# 1 Introduction

This paper investigates whether or not wage differentials exist between part-time and full-time workers in South African Labour market and moreover, whether this difference is attributable to the number of weekly hours worked or to differences in personal characteristics. In isolating the treatment effect of working part-time on wages, factors that influence selection into part-time employment are controlled for using the parametric Oaxaca-Blinder (1973) decomposition; the non-parametric Nopo (2004) matched decomposition; the Propensity Score Matching and Inverse Probability Weighting techniques.

In most countries, a wage penalty to part-time employment of between 10% and 30% is observed (Muller and Posel, 2008). Specifically, Hu and Tijdens (2003) compare wage differentials between Great Britain and the Netherlands and find no substantial difference in wages between part-time and full-time workers in the Netherlands but a wage penalty to part-time workers in Great Britain. Their finding implies that the outcome is largely dependent on the characteristics of the individuals being evaluated. Many other studies have also designated heterogeneity in the individuals as the factor determining wage differentials. For instance, Pratap and Quintin (2006) use semi-parametric propensity score matching techniques on panel data and find no evidence of wage differentials between formal and informal sectors workers in Argentina. Furthermore, Badaoui et al. (2008) equally find no evidence of an earnings premium for formal sector workers in South Africa once they control for unobserved heterogeneity. On the other hand Botelho and Ponczek (2011) use Ordinary Least Squares (OLS) and find a large premium for formal sector workers in Brazil. However, the size of the premium becomes smaller when they deploy a fixed effects regression to control for unobserved, time invariant heterogeneity.

In the South African context, investigating wage differentials between part-time and full time workers is relevant as unemployment is rife and a large number of South Africans only have access to

part-time employment. Further, those engaged in part-time employment are generally women and the previously disadvantaged whose wages need to be raised in order to obtain a less unequal society. To date Muller and Posel (2008) and Muller (2009) are the only two papers to have examined the South African part-time/full-time wage gap.

Therefore this paper contributes to the existing debate by providing a view of the part-time/full-time wage gap six years on from Muller and Posel (2008) and 4 years on from Muller (2009). In addition, the study employs different statistical techniques to re-examine the impact of the choice of hours worked on the wage rate using a dataset extracted from Wave 2 (2010/2011) of the National Income Dynamics Survey (NIDS) database for South Africa. In fact, using matching methods to compare differential returns to the number of hours worked has not been attempted in the South African context. However, unlike Muller and Posel (2008), this study uses a full sample of men and women to evaluate the wage differentials between part-time and full-time workers, as men are increasingly finding themselves taking on part-time employment in a climate of high unemployment. However, this paper does not explore gender gaps within the part-time/full-time conundrum. Workers are classified as part-time if they work less than 35 hours per week and full-time if they work in excess of 35 hours per week.

This paper is organized as follows; Section 2 describes the data while Section 3 outlines the four different econometric techniques used. Section 4 discusses the results and Section 5 concludes the paper, providing ideas for future research.

## **2 Data and Descriptive Statistics**

This study makes use of Wave 2 (2010/2011) of the National Income Dynamics Survey (NIDS); which is implemented by the Southern Africa Labour and Development Research Unit (SALDRU); as a cross-sectional dataset. The survey captures information for over 31,163 individuals in 7,301

households. The sample is restricted to individuals aged 15-59, working less than 113 hours a week and there are 19, 991 total observations but only 4, 691 wage observations. The following main variables controlling for individual characteristics were selected, in keeping with Muller and Posel (2008) and specifically with Hu and Tijdens (2003) who find that the wages of part-time and full-time workers are largely dependent on the characteristics of the individuals being evaluated.

Table 1: **Description of Variables**

<b>Variables</b>	<b>Description</b>
<i>hrlywage</i>	Hourly wage - Outcome
<i>parttime</i>	1 if respondent works < 35 hours a week – Treatment
<i>gender</i>	1 if respondent is male
<i>age</i>	Continuous variables representing experience
<i>edu</i>	Education level
<i>married</i>	1 if respondent is married
<i>numchil</i>	Number of children the respondent has

### ***1.1 Variable Measurement and Justification***

There is a huge body of theoretical and empirical literature that accounts for the existence of the observed wage differentials in a typical labour market setting. We use this evidence to provide a justification for the choice of variables used in this study.

*Part-time:* We hypothesize a negative relationship between part-time employment and the hourly wage rate based on a number of factors. A penalty to part-time workers is attributable to the following: (a) employers facing fixed hiring costs regardless of hours worked, making the hiring of part-time workers less attractive, (b) part-time workers have less mobility due to their not being breadwinners and (c) part-time workers are provided with less training by employers who are not willing to invest in them (Hirsch (2004), Rodgers (2004)).

*Education and Age:* The inclusion of the education variable is derived from the human capital theory of Becker (1962), and Mincer (1962) who emphasize the role of schooling, training, experience and other productivity-related factors in influencing earnings. Education and age (a proxy for

experience) have a positive effect on wages, as it increases the earning capacity of an individual through its effect on productivity. Therefore, this study also hypothesizes a positive relationship between the hourly wage rate and the level of educational attainment. When Muller and Posel (2008) control for the following; that part-time workers may have less education, that they have less work experience and that they may be concentrated in certain kinds of jobs, the size of the penalty is observed to fall but typically remains negative. Part-time wage penalties also tend to be smaller for both men and women early in their careers but tend to rise over time with workers most likely to be observed in part-time employment accumulating relatively less human capital (Hirsch, 2005).

*Gender:* Mincer and Polachek (1974) and Becker (1971) contend that gender wage gaps can be attributed to differences in individual characteristics. For instance, Mincer and Polachek (1974) stress the deterioration of women's human capital during periods of intermittency say when they have to take maternity leave as a negative influence on their ability to attract a high wage rate. Furthermore, Polachek (1981) and O'neill (2005) argue that it is due to these interruptions that women enter into those occupations where the cost of interruption is low, flexible work schedules are allowed, a less stressful work environment is present, however, occupations are more likely to be associated with lower wage rates. Women are therefore likely to earn less than men. We hypothesize a positive relationship between the gender variable and the hourly wage rate.

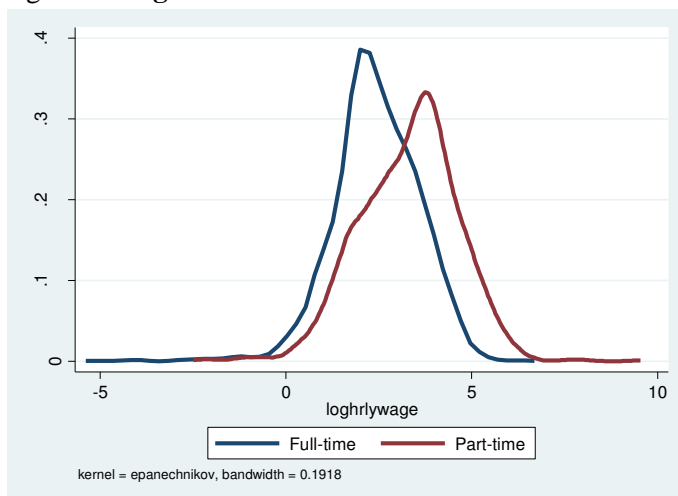
*Married:* This variable is a proxy for marital status. In the study, we expect a positive relationship between the hourly wage rate and marital status. This is motivated by the argument that couples usually have a higher household expenditure than their unmarried counterparts. Thus the former have an incentive to earn higher wages. Previous studies have shown that, marriage has positive effects on a person's wage rate [see Chen and Hamori, (2008ab); Xie and Yao, (2005)].

*Children*: The relationship between the children and the workers' wage rate has not received much attention in studies on wage differentials. Previous studies, have found that child bearing women earn lower hourly wages than those without children due to the need to balance between work and family as time and effort are needed for children rearing. Consequently, their preference is for temporary and part-time employment [Hill, (1979); Waldfogel, (1997)]. In this study, we expect a negative relationship between the variable *Children* and the hourly wage rate.

### 1.2 Descriptive Statistics

Figure 1 depicts the wage density functions for part-time and full-time workers in 2010/2011, where the full-time density function lies to the left of the part-time density function, implying a wage premium to part-time workers.

Figure1: **Wage Densities for Part-time and Full-time Workers**



The statistics in Table 2 describe the data, specifically, the variables that are used. The sample means of hourly wage, age and education are R38.83 per hour, 31.97 of age and 8.94 years of schooling respectively.

**Table 2: Summary Statistics**

Variable	Obs	Mean	Std. Dev.	Min	Max
<i>Hourly Wage</i>	4691	38.829	219.128	0.01	13954.22
<i>Gender</i>	19991	-----	-----	0.00	1.00
<i>Age</i>	19991	31.975	12.693	15.00	59.00
<i>Education</i>	16097	8.936	4.131	0.00	23.00
<i>Marital Status</i>	15266	-----	-----	0.00	1.00
<i>Number of Children</i>	19990	0.807	1.512	0.00	12.00

The mean differences between part-time and full-time workers appear in Table 3 with the differences in all tested characteristics of part-time and full-time workers being significantly different but to varying degrees. We see that not only do part-time workers earn a significant premium; they are also younger and have significantly lower educational attainment; which is in line with expectations that part-time workers are expected to have less education and less work experience (Age is the proxy variable) than full-time workers (Muller and Posel, 2008).

**Table 3: Mean Difference and T-test Results**

	Full-time	Part-time	Difference	t-value	$Pr(T < t)$
<i>Hourly Wage</i>	20.811	68.038	-47.226	-7.03	0.0000
<i>Age</i>	37.251	31.008	6.243	25.58	0.0000
<i>Education</i>	10.133	2.592	7.541	17.77	0.0000
<i>Number of Children</i>	0.996	0.773	0.223	7.57	0.0000

*Source: Authors' calculations.*

### 3 Methodology

Four techniques controlling for differences in characteristics between part-time and full-time workers were utilized in this study to understand how the choice of working hours explains wage differentials between these two groups. The Oaxaca-Blinder decomposition disaggregates the mean differences in

wages based on linear regression models in a counterfactual manner (Jann, 2008). However, one of the drawbacks of this technique is its inability to separate individuals falling in the common support region from individuals falling out-of-the support region, which may generate biased results. An alternative procedure is the Nopo (2004) Decomposition Method that allows comparisons of results over the common support and the identification of the primary contributors to the wage differentials. PSM and IPW also use the common support but by using the propensity score as a basis to evaluate the treatment effects.

### 3.1 *The Oaxaca-Blinder Decomposition*

The Oaxaca-blinder decomposition is used to decompose the mean differences in wages based on linear regression models using a counterfactual (Jann, 2008). The wage differential between two groups is divided into two components: the *explained* portion which is explained by group differences in observable characteristics and the *unexplained* or *residual* portion that cannot be accounted for by such differences in wage differentials (Jann, 2008).

To explore the wage differentials between part-time (P) and full-time employment (F), ordinary least squares is used to estimate two separate wage regressions for individuals who work part-time and full-time:

$$W_i^P = \alpha^P + \beta X_i^P + \varepsilon_i \tag{1}$$

$$W_i^F = \alpha^F + \beta X_i^F + \varepsilon_i \tag{2}$$

Equation (1) can be described as the part-time wage equation and equation (2) can be described as the full-time wage equation where  $W_i$  represents the hourly wage of individual  $i$ ,  $X_i$  is a vector of individual, job and industry parameters and  $\varepsilon_i$  is the error term (Muller and Posel, 2008).

Average wage differentials between part-time and full-time employment can be decomposed as follows:

$$\overline{W}_i^F - \overline{W}_i^P = \sum_i^n \hat{\beta}^F (\bar{X}^F - \bar{X}^P) + \sum_i \{ (\hat{\alpha}^F - \hat{\alpha}^P) \bar{X}^P (\hat{\beta}^F - \hat{\beta}^P) \} \quad (3)$$

The term on the left hand side of equation (3) can be defined as the gap in mean wages between part-time and full-time workers. The first term on the right hand side of equation (3) is the *explained* portion that can be explained by differences in the observable characteristics of the two samples. The remaining term is the *unexplained* portion of the wage differential, or the portion attributable to how differences in characteristics are *rewarded*, which is attributable to omitted variables or a breakdown in the labour market (Muller and Posel, 2008). In other words, it represents the counterfactual wage for women if they were paid as men. Though simple to apply, the Oaxaca-Blinder decomposition suffers from many drawbacks (Djurdjevic and Radyakin, 2005). First, it does not make use of any statistic other than the mean. Secondly, the method is based on the very restrictive assumption of linearity between the outcome variable  $W$  and the covariates  $X$ ; thus, it might not provide consistent estimates when the conditional mean is a non-linear function. Thirdly, in the presence of non-random sample selection, or when endogeneity arises, the method will give inconsistent estimates. And finally, in constructing the counterfactual wage, the assumption is made that the estimates of the wage equations are valid out of the common support of the distributions of the covariates, which may not be true and therefore lead to the decomposition being invalid.

### **3.2 The Nopo (2004) Matched Decomposition**

Nopo (2004) developed a nonparametric alternative procedure that accounts for the differences in the treatment variable (gender or any other) in the *distribution* of individual characteristics. Nopo's approach uses statistical matching to separate the sample of part-time and full-time workers into 2 subsamples: workers who share a common support and those who do not. Because no assumption of

validity on the out-of-support region is imposed, this procedure presents the advantage that the counterfactual wage is simulated only over the common support region (Khitarihvili, 2013).

Let  $g^{PT}(x) = E(W / PT)$  be the average wage for part-time workers with characteristics  $X$ ,  $F^{PT}(x)$  the cumulative function of individual characteristics  $X$  among part-time, and  $S^{PT}$  the support of the distribution of characteristics for part-time employees (Nopo, 2004). Let's also define

$g^{FT}(x) = E(W / FT)$ ,  $F^{FT}(x)$  and  $S^{FT}$  similarly for full-time workers.

Let  $S = (S^{PT} \cap S^{FT})$  be the common support and  $p_{S/PT} = p(X \in S / PT) = \int_S dF^{PT}(x)$  be the probability

measure of the set  $S$  under the distribution  $dF^{PT}(\cdot)$ . Then we can divide the population of part-time workers into two subpopulations of individuals having characteristics that belong either to the common support  $S$  or to the out of the common support  $\bar{S}$ :

$$\begin{aligned} E(W / PT) &= E_S(W / PT)p_{S/PT} + E_{\bar{S}}(W / PT)p_{\bar{S}/PT} \\ E(W / PT) &= p_{\bar{S}/PT}[E_{\bar{S}}(W / PT) - E_S(W / PT)] + E_S(W / PT) \end{aligned} \quad (4)$$

Similarly for full-time workers, we obtain:

$$E(W / FT) = p_{\bar{S}/FT}[E_{\bar{S}}(W / FT) - E_S(W / FT)] + E_S(W / FT) \quad (5)$$

The overall wage gap between part-time and full-time employees  $\Delta$  can be written as:

$$\begin{aligned} \Delta &= E(W / m) - E(W / f) \\ &= \underbrace{[E_S(W / PT) - E_S(W / FT)]}_I + \underbrace{p_{\bar{S}/PT}[E_{\bar{S}}(W / PT) - E_S(W / PT)]}_II + \\ &\quad \underbrace{p_{\bar{S}/FT}[E_{\bar{S}}(W / FT) - E_S(W / FT)]}_III \end{aligned} \quad (6)$$

The first term of the right hand side represents the differences of wages between part-time and full-time workers over the common support only; the second term (resp. the third) captures the wage differences

between part-time (resp. full-time) workers in and out of the support. The first term of equation (6) can be decomposed as in the Blinder-Oaxaca decomposition by adding and subtracting the counterfactual mean wage ( $\int_S g^{PT}(x) dF_S^{FT}(x)$  with  $dF_S^{FT}(x)$  being the density of characteristics in the subpopulation of full-time workers belonging to the common support  $\bar{S}$ ). This leads to the following expression:

$$E_S(W / PT) - E_S(W / FT) = \int_S g^{PT}(x) [dF_S^{PT}(x) - dF_S^{FT}(x)] + \int_S [g^{PT}(x) - g^{FT}(x)] dF_S^{FT}(x) \quad (7)$$

The first and second terms of equation (7) represent the ‘Endowment’ and ‘Remuneration’ effects of the wage gap but on the common support only. As a consequence, the Nopo’s four component decomposition can be written as:

$$\Delta = \Delta_x + \Delta_0 + \Delta_{PT} + \Delta_{FT} \quad (8),$$

where  $\Delta_x = \int_S g^{PT}(x) [dF_S^{PT}(x) - dF_S^{FT}(x)]$ ,  $\Delta_0 = \int_S [g^{PT}(x) - g^{FT}(x)] dF_S^{FT}(x)$ ,

$$\Delta_{PT} = p_{\bar{S}/PT} [E_{\bar{S}}(W / PT) - E_S(W / PT)] \text{ and } \Delta_{FT} = p_{\bar{S}/FT} [E_{\bar{S}}(W / FT) - E_S(W / FT)]$$

$\Delta_x$  represents the portion of the gap that can be explained by differences in the distribution of human capital variables between part-time and full-time workers over the common support;  $\Delta_0$  captures the residual part of the wage differential;  $\Delta_{PT}$  stands for the part of the wage differential that can be explained by differences between part-time workers in and out of the common support; finally,  $\Delta_{FT}$  can be defined in the same manner for full-time workers in and out of common support.

### 3.3 Propensity Score Matching

The factors explaining the wage differentials can be identified by isolating the causal effect of working in part-time employment on hourly wages. In line with Muller and Posel (2008), part-time employment is taken to be for employees working less than 35 hours per week and use it as the ‘treatment’ variable. The control group is constituted with employees working more than 35 hours per week. We then define the counterfactual as the wage a full-time worker would have earned if he/she was employed as a part-time worker and vice versa. The study uses different propensity score methods in investigating the earnings differentials between part-time and full-time employees in South Africa. First, we employ simple regression based on mean differences before delving into the different matching techniques. Secondly, we use the Propensity Score Matching approach by Rosenbaum & Rubin (1983) which entails forming matched sets of treated and untreated subjects who share a similar value of the propensity score. Formally, let’s define:

Treatment:  $D_i = 1$  if part-time and  $D_i = 0$  if full-time;

Outcome:  $Y_{1i}$  = hourly wage for part-time workers and  $Y_{0i}$  = hourly wage for full-time workers

The difference between  $Y_{1i}$  and  $Y_{0i}$  is the causal effect of working part-time on individual  $i$ ’s outcome and can be expressed as:

$$Y_i = (1 - D_i)Y_{0i} + D_iY_{1i} \text{ or } Y_i = Y_{0i} + (Y_{1i} - Y_{0i})D_i \quad (9)$$

In our analysis, we only get to see one of the outcomes  $Y_{1i}$  or  $Y_{0i}$  as both potential outcomes cannot be observed on the same individual. We therefore measure the average of  $Y_{1i} - Y_{0i}$  or the average for some group, such as those who work on a part-time basis. That is:  $E[Y_{1i} - Y_{0i} | D_i = 1]$ . This expression denotes the *average treatment on the treated (ATT)*. The comparison of average earnings conditional on number of hours worked is formally linked to the average causal effect by the following equation.

$$\begin{aligned}
\underbrace{E[Y_i | D_i = 1] - E[Y_1 | D_i = 0]}_{\text{Observed difference in earnings}} &= \overbrace{E[Y_{1i} | D_i = 1] - E[Y_{01} | D_i = 1]}^{1. \text{ ATT}} + \\
\underbrace{E[Y_{01} | D_i = 1] - E[Y_{01} | D_i = 0]}_{2. \text{ Selection Bias}} &
\end{aligned} \tag{10}$$

The first term on the right hand side of equation (10) captures the causal effect which is the difference between the averages earnings of part-time workers and those of workers with the same characteristics who are full-time workers. The second term captures the selection bias effect which is the difference between the counterfactual for part-time workers and the observed outcome for the full-time employees. If selection bias is positive, *ATT* exaggerates the outcomes of being in part-time employment. The *average treatment effect* (ATE), denoted as  $E(Y_1 - Y_0)$  is a weighted average of the treatment effects for the treated and non-treated. A number of matching algorithms were used as briefly discussed below:

The *Nearest Neighbour* PSM estimates matches for all treated units, however, these matches may be inferior because for some treated units the nearest neighbor may have a very different propensity score.

It is denoted by:  $C_j(\hat{e}_{1i}) = \|\hat{e}_{1i} - \hat{e}_{0i}\|$  (11)

The next matching algorithm is the *Nearest-Neighbour* with *Caliper* which is expressed as:

$$C_j(\hat{e}_{1i}) = \min_{j \in i_0} \|\hat{e}_{1i} - \hat{e}_{0i}\| \tag{12}$$

Note that  $\varepsilon = 0.25\sigma_e$ , in other words it is one fourth of the standard deviation of the propensity scores (Koch, 2013).

The *Kernel* estimation technique makes use of weighted averages of the untreated to construct the counterfactual. Due to more information being used, it achieves lower variances but the downside is that bad matches may be used due to this need for more information (Caliendo Kopenieg, (2006)).

$$\hat{E}(Y_{0i} | P(X_i), D_i = 0) = \frac{1}{x} \sum_{\substack{j=1 \\ \{D_j \in A_x\}}}^x Y_{0j} \quad (13)$$

The *Mahalanobis* PSM estimator scales the distance to the variance in each observation based on the covariance matrix (Posner and Ash). If  $i$  and  $j$  are two observations from the same distribution with a covariance matrix  $C$ , where  $i$  is the first treated observation and  $j$  are the control observations, then the Mahalanobis distance is as follows:  $d_{ij}=(x_1 - x_0)'C^{-1}(x_1-x_0)$  (14),

where  $x$  are covariates that explain the treatment (Koch, 2013). It is particularly useful as it takes into account correlation of the dataset and is invariant to the size of the sample (Rosenbaum and Rubin (1983)).

### 3.4 Inverse Probability Weighting

*Inverse probability weighting* (IPW) uses weights based on the propensity score to create a synthetic sample in which the distribution of measured baseline covariates is independent of the treatment assignment. The use of IPW is similar to the use of survey sampling weights that are used to weight survey samples so that they are representative of specific populations (Morgan & Todd, (2008)). Let  $y_i$  be an indicator variable denoting whether or not the  $i^{th}$  subject was treated; furthermore, let  $p_i$  denote the propensity score for the  $i^{th}$  subject. The First moment for the treated can be defined as

$$\bar{y} = \frac{\sum_i^N y_i / p_i}{\sum_i^N 1 / p_i}, \quad (15)$$

A subject's weight is equal to the inverse of the probability of receiving the treatment that the subject actually received.

## 4 Analysis

The analysis begins by first employing the Oaxaca-Blinder decomposition to analyze the effect of part-time employment on wages. Thereafter the Nopo decomposition results are presented, followed by propensity score matching and inverse probability weighting.

### 4.1 Oaxaca Decomposition Results

In Table 4, the average hourly wages for full-time and part-time workers are R 20.61 and R67.76 respectively. Thus, on average, part-time workers in South Africa earn R 47.16 per hour more than full-time workers. Part-time workers would earn R8.65 less than full-time workers if they had the same characteristics as full-time workers. In other words, full-time workers have some characteristics not observed among part-time workers, and these characteristics are not favourably rewarded on the Labour market. When applying full-time workers coefficients to part-time workers characteristics, part-time workers average hourly wages increase by R 49.25, amount that captures the pure *unexplained* wage premium faced by part-time workers. The simultaneous effects of endowments and coefficients yield an R 6.47 increase in average hourly wages for part-time workers.

Table 4: Oaxaca Decomposition Results

<i>Dependant variable: Hourly wage</i>				
	<i>Mean</i>	<i>Std. Err.</i>	<i>Z-value</i>	<i>Pr (Z &lt; z)</i>
<i>Full-time</i>	20.60708	0.53258	38.69	0.0000
<i>Part-time</i>	67.76372	9.405831	7.2	0.0000
<i>Difference</i>	-47.1566	9.420897	-5.01	0.0000
<i>endowments</i>	8.566203	2.655268	3.23	0.0010
<i>coefficients</i>	-49.2519	9.390743	-5.24	0.0000
<i>interaction</i>	-6.47091	2.495534	-2.59	0.0100

**Source:** Authors' calculations

#### 4.2 *Nopo Estimation results*

Considering that the overall wage differential is R 47.22, the hourly wage of a part-time employee in SA is 226.92% higher than that of a full-time employee. This may be indicative either of a labour market in which there are important inequalities in remunerations, or of the fact that policies designed at correcting for discrimination against part-time employees have had deeper effects than anticipated. In an attempt to explain this important earnings differential, we implemented the Nopo (2004) matching decomposition method, where the matching is based on demographic characteristics included in sequential order. Table 5 reports the estimated results.

**Table 5: Nopo Decomposition Results**

	Age	Education	Children	Gender	Full Set	Full set (%)
$\Delta$	226.92%	226.92%	226.92%	226.92%	226.92%	1
$\Delta_0$	222.11%	246.27%	265.58%	266.27%	274.51%	120.97
$\Delta_{PT}$	-0.36%	-1.33%	-48.55%	-45.17%	-60.06%	-26.47
$\Delta_{FT}$	-----	-3.80%	-9.21%	-9.16%	-9.23%	-4.07
$\Delta_x$	5.17%	14.22%	19.1%	14.98%	21.72%	9.57
% Matched						
Part-time	99.87%	96.80%	73.30%	69.91%	59.48%	
Full-time	100.00%	91.38%	65.02%	61.70%	49.79%	
$SE, \Delta_0$	7.61%	9.48%	3.85%	3.40%	-----	

**Source:** Authors' calculations

It can be noted that the component representing the remuneration effect ( $\Delta_0$ ) dominates in explaining the pay differential. The other components  $\Delta_{FT}$ ,  $\Delta_{PT}$  and  $\Delta_x$  play a less important role in explaining the wage gap between part-time and full-time workers.

Component  $\Delta_{PT}$  is consistently negative across the sequential sets of variables included (- 26.47% for the full set) and refers to the portion of the wage gap that would have disappeared if the unmatched part-time workers had on average the same wages as the matched part-time employees. In other words, the differences in characteristics between matched and unmatched part-time workers contract the wage gap by 26.47% (or 60 percentage points). This component can also be interpreted as a ‘crude measure of the full-time workers disadvantage in access to particular combination of characteristics which are rewarded on the market’ (Djurdjevic and Radyakin, 2005).

Component  $\Delta_{FT}$  is also consistently negative. Based on the full set of specifications, this component indicates that the differences between matched and unmatched full-time workers characteristics reduce the wage gap by 4.07% (9.23 percentage points). This finding suggests that full-time workers displaying characteristics that cannot be matched to part-time workers are earning more than their counterparts whose characteristics were matched. Though the unmatched wage gaps  $\Delta_{FT}$  and  $\Delta_{PT}$  are much smaller in magnitude than  $\Delta_0$ , they might convey important information concerning the potential existence of pre-market discrimination against full-time employees.

The distributional gap  $\Delta_x$  stands at 21.72% (full set), and expresses the expected reduction in the wage gap if the characteristics of all the part-time and full-time workers were equally distributed.

It is also worth noting that the proportions of part-time and full-time workers that can be matched based on the full set of demographic characteristics stand at 59.48% for the part-time workers and at 49.79% for the full-time workers. Given these low matching rates, Propensity Score Matching is used in the next section to determine whether other matching techniques may improve the share of individual on the common support, which in turn results with better estimates of the treatment effects.

### 4.3 Propensity Score Matching

For the propensity matching analysis, a simple mean difference between the part-time and full-time groups is estimated and a t-test is conducted on this mean difference to see whether the difference is significant. Then an ANOVA test is used to gauge covariate balance and determine whether matching is required. This is followed by regression analysis and thereafter, matching. A variety of Propensity Score Matching (PSM) estimators are used to match the observations. The results thereof are t-tested and tested for sensitivity.

#### 4.3.1 Mean Difference Estimation

We are interested in determining whether there exists a significant wage differential between part-time and full-time workers and the results thereof are summarized in Table 6. The hypotheses to be tested are:  $H_0$ : There is no significant wage differential;  $H_1$ : The wage differential is significant.

Table 6: Mean Difference and T-tests Results

	<i>Obs</i>	<i>Mean</i>	<i>Std. Err.</i>	<i>t-value</i>	<i>Pr (T &lt; t)</i>
<i>Full-time</i>	3099	20.8114	0.5358		
<i>Part-time</i>	1592	68.0377	9.3218		
<i>Difference</i>		-47.2263	6.7223	-7.03	0.0000

**Source:** Authors' calculations

The p-value = 0.0000 <  $\alpha$  = 0.05 indicates that there is enough evidence to reject the null hypothesis. In other words, there is a wage premium in favour of part-time employees of R 47 per hour. However, this conclusion is not necessarily valid as the groups used for testing the treatment effect are likely to suffer from selection bias.

#### 4.3.2 Covariate Balance Test

In order to determine whether the PSM is successful in balancing the covariates between the treated and the untreated groups, it is necessary to run a test of equality of means for each covariate between full-time and part-time workers *before* the implementation of Propensity Score Matching. The results of

these tests appear in Table 7 and will later be compared to those conducted on the same covariates after matching.

**Table 7: ANOVA Results**

	df	Sum Sq	Mean Sq	F Value	Prob (>F)
<i>gender</i>	1	8.5526	8.5526	62.47	0.0000
<i>numchil</i>	12	8.0402	0.6700	4.89	0.0000
<i>age</i>	44	127.8062	2.9047	21.22	0.0000
<i>edu</i>	16	100.5070	6.2817	45.89	0.0000
<i>married</i>	1	4.20775866	4.2078	30.74	0.0000
<i>Residuals</i>	15116	2069.3748	0.1368996		

**Source:** Authors' calculations

The null hypothesis of no mean difference in gender, the number of children, age, education and marital status between part-time and full-time workers is rejected at a 1% level of significance, which is clear evidence of covariate imbalance between the two groups. There is a need to adjust any difference in outcome for differences in covariates. This can be achieved either via the specification of a conditional model for the potential outcome (Regression Analysis) or by using matching techniques that have the advantage of avoiding model dependence.

### 4.3.3 Regression Analysis

In this section, we present the results of regression adjusted wage equation that will be compared to the results of propensity score matching. The first regression is a simple linear regression aiming at determining the impact of the treatment on hourly wage. The second regression conducted is a multiple regression that includes several covariates together with the treatment variable to determine their impact on the wage. The results are summarized in Table 8:

**Table 8: Regression Analysis**

<i>Dependent variable: Hourly wage</i>		
	(1)	(2)
<i>parttime</i>	47.23*** (-7.03)	51.44*** (-7.58)
<i>gender</i>		5.516 (-0.59)
<i>numchil</i>		-4.688 (-1.49)
<i>age</i>		1.327*** (-3.71)
<i>edu</i>		3.923*** (-4.49)
<i>married</i>		19.54*** (-2.6)
<i>Constant</i>	20.81*** (-5.31)	-72.03*** (-3.91)
<i>Observations</i>	4,691	4,648
<i>R-squared</i>	0.010	0.022

*t*-statistics in parentheses \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

**Source:** Authors' calculations

The simple regression estimate indicates a significant wage premium of R 47.23 in favour of part-time workers. The result confirms the earlier one obtained from the mean difference test in Table 6. With the inclusion of the covariates, the results of the hourly wage increase to R 51.44 up from R47.2 as earlier on reported in column 1 of Table 8. In fact, the premium remains significant at a 1% level. The remaining coefficients are all significant except for the gender variable.

Regression analysis however does not take overlapping into consideration, and if the difference between the average values of the covariates in the two groups is large, the results are sensitive to the linearity

assumption (Caliendo and Kopeinig, (2008)). Because of this limitation of regression, it is recommended to make use of several matching techniques instead, in order to obtain better results.

#### 4.3.4 Empirical implementation of Propensity Score Matching and Covariate Balancing

We start by estimating the propensity score using a probit function of the treatment on the covariates. The estimation process is repeated for each of the following matching algorithms: Nearest Neighbour, Caliper matching, Kernel and Mahalanobis. The results are summarized in Table 9.

Table 9: Average Treatment effect on the Treated using PSM

<i>Matching algorithm</i>	<i>Outcome Variable</i>	<i>Sample</i>	<i>Treated</i>	<i>Controls</i>	<i>Difference</i>	<i>t-stat</i>
<i>Nearest neighbour</i>	<i>hrlywage</i>	<i>Unmatched</i>	67.76	20.61	47.16	6.96
		<i>ATT</i>	67.76	16.15	51.62	5.45
		<i>ATU</i>	20.61	69.54	48.94	
		<i>ATE</i>			49.85	
<i>Caliper matching</i>	<i>hrlywage</i>	<i>Unmatched</i>	67.76	20.61	47.16	6.96
		<i>ATT</i>	67.76	16.15	51.62	5.45
		<i>ATU</i>	20.61	69.54	48.94	
		<i>ATE</i>			49.85	
<i>Kernel</i>	<i>hrlywage</i>	<i>Unmatched</i>	67.76	20.61	47.16	6.96
		<i>ATT</i>	67.76	18.31	49.45	5.26
		<i>ATU</i>	20.61	74.26	53.65	
		<i>ATE</i>		63.61	52.23	
<i>Mahalanobis</i>	<i>hrlywage</i>	<i>Unmatched</i>	67.76	16.86	47.16	6.96
		<i>ATT</i>	67.76	20.61	50.90	5.37
		<i>ATU</i>	20.61	77.57	56.89	
		<i>ATE</i>			54.86	

**Source:** Authors' calculations

The Caliper and Nearest Neighbour matching techniques yield identical results. The Kernel and Mahalanobis matching techniques give us slightly different results from the first two. For each matching algorithm, it can be noted that before matching, the wage differential between the two groups of workers is about R 47, and in each case the wage differential is statistically significant. After matching, for all the matching algorithms, the wage differential increases and remains statistically significant. This provides enough evidence for us to state that conditional on the propensity score, workers who are part-time employees earn on average R 49 to R52 more than their full-time counterparts. Next, we perform

statistical tests that allow us to determine whether the propensity score adequately balances the characteristics between the two groups of workers under comparison, and which matching algorithm yields the best results.

Table 10: Covariate balancing under PSM

<i>Matching algorithm</i>	<i>Variables</i>	<i>Sample</i>	<i>Mean</i>		<i>% bias</i>	<i>% reduction in bias</i>	<i>p-value</i>	
			<i>Treated</i>	<i>Controls</i>				
<i>Nearest neighbour</i>	<i>gender</i>	Unmatched	.45	.53	-16.7		0.000	
		Matched	.45	.46	-3.7	77.9	0.301	
	<i>numchil</i>	Unmatched	1.22	.99	14.7		0.000	
		Matched	1.22	1.16	3.4	76.7	0.348	
	<i>age</i>	Unmatched	37.46	37.22	2.2		0.473	
		Matched	37.46	36.59	8.1	-264.6	0.024	
	<i>edu</i>	Unmatched	9.16	9.71	-13.9		0.000	
		Matched	9.16	9.11	1.1	92.4	0.770	
	<i>married</i>	Unmatched	.30	.35	-10.0		0.001	
		Matched	.30	.28	4.6	54.1	0.184	
	<i>Caliper matching</i>	<i>gender</i>	Unmatched	.45	.53	-16.7	-	0.000
			Matched	.45	.46	3.7	77.9	0.301
<i>numchil</i>		Unmatched	1.22	.99	14.7		0.000	
		Matched	1.22	1.16	3.4	76.7	0.348	
<i>age</i>		Unmatched	37.46	37.22	2.2		0.473	
		Matched	37.46	36.59	8.1	-264.6	0.024	
<i>edu</i>		Unmatched	9.16	9.71	-13.9		0.000	
		Matched	9.16	9.11	1.1	92.4	0.770	
<i>married</i>		Unmatched	.30	.35	-10.0		0.001	
		Matched	.30	.28	4.6	54.1	0.184	
<i>Kernel</i>		<i>gender</i>	Unmatched	.45	.53	-16.7		0.000
			Matched	.45	.46	-2.8	82.9	0.423
	<i>numchil</i>	Unmatched	1.22	.99	14.7		0.000	
		Matched	1.22	1.13	5.9	60.1	0.105	
	<i>age</i>	Unmatched	37.46	37.22	2.2		0.473	
		Matched	37.46	36.93	4.9	-122.3	0.169	

	<i>edu</i>	Unmatched	9.16	9.71	-13.9		0.000
		Matched	9.16	9.37	-5.4	60.9	0.129
	<i>married</i>	Unmatched	.30	.35	-10.0		0.001
		Matched	.30	.30	1.2	88.2	0.735
	<i>gender</i>	Unmatched	.45	.53	-16.7		0.000
		Matched	.45	.45	0.0	100.0	1.000
	<i>numchil</i>	Unmatched	1.22	.99	14.7		0.000
		Matched	1.22	1.22	0.2	98.6	0.955
<i>Mahalanobis</i>	<i>age</i>	Unmatched	37.46	37.22	2.2		0.473
		Matched	37.46	37.41	0.4	79.7	0.901
	<i>edu</i>	Unmatched	9.16	9.71	-13.9		0.000
		Matched	9.16	9.16	-0.1	99.4	0.982
	<i>married</i>	Unmatched	.30	.35	-10.0		0.001
		Matched	.30	.30	0.0	100.0	1.000

**Source:** Authors' calculations

It appears that the Mahalanobis matching algorithm produces the best results as all the post-matching bias percentages are less than 5%. There is enough evidence to infer that the PSM allows for the generation of a group which is as close as desired to the Treatment group and that can be used for the estimation of the Average Treatment Effect for the Treated.

#### **4.4 Inverse Probability Weighting**

In Table 11, we use the Inverse the Probability Weighting Estimator to investigate the impact of part-time employment in the hourly wage in South Africa. In contrast to the Mahalanobis matching algorithm described earlier, IPW uses estimated probability weights to correct for the missing-data problem which arises from the fact that each individual is observed in only one of the potential outcomes. Hence, the IPW estimator uses a two-step approach to estimating treatment effects. First, it estimates the parameters of the treatment model and computes the estimated inverse probability weights. Second, it uses the

estimated inverse-probability weights to compute weighted averages of the outcomes for each treatment level. The contrasts of these weighted averages provide the estimates of the ATE. Using this weighting scheme, corrects for the missing potential outcomes.

Table 11: **IPW Regression Results**

<i>Dependent Variable: Hrlywage</i>		
Variable	ATE	ATT
<i>parttime</i>	47.90*** (6.258)	52.13*** (8.296)
<i>gender</i>	10.56 (0.993)	3.275 (0.433)
<i>numchil</i>	-5.829* (-1.727)	-3.790 (-1.410)
<i>age</i>	1.612*** (3.875)	1.100*** (3.943)
<i>edu</i>	4.586*** (4.593)	3.763*** (5.395)
<i>married</i>	26.03*** (2.910)	14.77** (2.556)
<i>Constant</i>	-90.55*** (-4.182)	-61.36*** (-4.215)
<i>Observations</i>	4,648	4,648
<i>R-squared</i>	0.019	0.025

*t*-statistics in parentheses \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

**Source:** Authors' Calculations

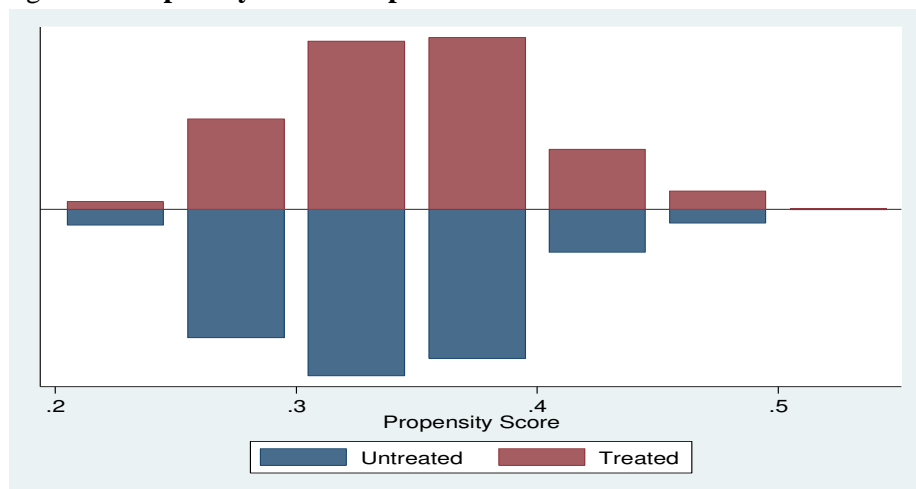
From the results in Table 11, we estimate the effect of working under part-time employment on the hourly wage or the Average Treatment Effect (*ATE*). The results show that workers employed on a part-time basis earn an average of R47.90 more than their full-time counterparts. Furthermore, as is the case with impact evaluation, we are concerned about those individuals that did in fact receive treatment, and we want to establish how much the outcome changes as a result of the treatment for that subpopulation. The Average Treatment effect on the Treated (*ATT*) therefore provides us with the solution. From our

results, among part-time workers, working part-time causes hourly wages to increase by an average of R52.13 than would have been the case if these workers had not been employed on a part-time basis.

#### 4.5 Common Support Condition

Another crucial step in our analysis is to check for the validity of the propensity score matching estimation using the common support or overlap condition. We assume that the probability of working part-time, conditional on observed characteristics, lies between 0 and 1 (implying participation is not perfectly predicted). The results from our propensity score matching are plotted in Figure 2.

Figure 2: Propensity Score Graph



Source: Authors' Calculations

Visual inspection suggests that the densities of the propensity scores are similar after matching. The plot also reveals a clear overlapping of the distributions. This implies that the common support condition is satisfied. The final percentage of individuals on common support is higher under PSM (100%), whereas Nopo (72%-78%) leaves out about a quarter of the individuals out of the common support which is quite substantial.

#### 4.6 Robustness Checks

In empirical analysis, it is important to evaluate the robustness of the estimations by assessing the performance of the different matching algorithms. Robustness checks help increase the reliability of the results by confirming that the estimation results do not depend crucially on the particular methodology chosen. To make sure that these findings are not driven by the selection of a particular technique, coefficients were estimated using different matching algorithms. The results of this robustness check are shown in Table 12.

Table 12: **Robustness Checks for Propensity Score Matching**

Matching Algorithm	ATT	ATU	ATE
Nearest Neighbour	51.6163388	48.9361107	49.8466271
SE	9.47160794***		
Caliper Matching	51.6163388	48.9361107	49.8466271
SE	9.47160794***		
Kernel Matching	49.4529738	53.6535586	52.2265527
SE	9.40695824***		
Mahalanobis	50.9012107	56.8906512	54.8559424
SE	9.47595698***		

**Source:** Authors' calculations

From the result, we can see that the impact on the hourly wage after matching does not appear to depend critically on the algorithm used. This is from the fact that both the value of the coefficients and their respective levels of significance are very similar using the different matching algorithms.

## 5 Conclusion

The study employed the different analytical approaches on the National Income Dynamics (NIDS) database for South Africa to investigate the relationship between the number of hours worked and individual hourly wage. The principal objective was to explain the causal relationship between number of hours worked and hourly wage and to deal with the problem of selection bias.

Considering that the sample used was obtained from a non-randomized observational study, the Oaxaca-Blinder Decomposition, the Nopo (2004) Matched Decomposition, Propensity Score Matching and Inverse Probability Weighting techniques were used to obtain estimates of wage differentials. The Oaxaca-Blinder results indicate an hourly wage premium of R 47, 16 to part-time employment. The Nopo Matched Decomposition results indicate an hourly wage premium of R 47.22, with a 'Remuneration' effect of 120.97% and a negative 'Endowment' effect of 20.97%. Using Propensity Score Matching, an hourly wage premium to part-time workers of R47.22 was obtained before matching and R50.90 after matching is achieved. The IPW technique yields a wage premium to part-time workers of R47.9 when using the Average Treatment Effect (ATE) as the weight and R52.93 when the Average Treatment Effect on the Treated (ATT) is used.

The PSM and IPW methods yielded better results due to their higher percentage of common-support cases. The propensity score was calculated conditional on the selection and outcome variables. In the balancing tests, there remains no difference in mean characteristics between treated and non-treated after matching.

The IPW technique pointed to a wage premium to part-time workers of R52.13 when using the Average Treatment Effect (ATE) as the weight and R47.90 when the Average Treatment Effect on the Treated (ATT) is used. From our findings, it can be concluded that matching conditional on propensity score of the observed covariates reduces difference in the hourly wage between part-time and fulltime

workers when compared to a simple OLS regression. The results are robust for different matching algorithms. After creating a counterfactual of the treated group it is found that the premium associated with working part-time increases. However, in contrast to PSM estimators which can only make use of observables, IPW uses estimated probability weights to correct for the missing-data problem which arises from the fact that each individual is observed in only one of the potential outcomes. Hence, the IPW uses weighted averages to provide the estimates of the ATE and ATT, correcting for the missing potential outcomes. This implies that the higher hourly wage for part-time workers is in itself higher than for full-time workers and is not conditional on observed workers' characteristics. This could be as a result of other factors prevailing in South Africa's labour market.

## 6. References

- BADAOU, E., STROBL, E. and WALSH, F. (2008). Is there an informal sector wage penalty? evidence from South Africa. *Economic Development and Cultural Change*, 56(1): 683-710.
- BATOOL, S. (2012). The establishment size-wage premium: an analysis using propensity score matching. PhD Thesis. Centre d'Economie de la Sorbonne.
- BECKER, G.S. (1962). Investment in human capital a theoretical analysis. *Journal of Political Economy, Supplement*, 70(5): S9-S49.
- BECKER, G.S. (1971). *The economics of discrimination*. The University of Chicago Press, Chicago.
- BECKER, S.O., and CALIENDO, M. (2007). Mhbounds - sensitivity analysis for average treatment Effects. *The Stata Journal*, 7 (1): 71-83.
- BOTELHO, F. and PONCZEK, V. (2011). Segmentation in the Brazilian labor market. *Economic Development and Cultural Change*, 59(2): 437- 463.
- CALIENDO, M., and KOPEINIG, S. (2006). *Some practical guidance for the implementation of propensity score matching*. IZA Discussion Paper No. 1588.
- CHEN, G.F. and HAMORI, S. (2008). An empirical analysis of gender wage differentials in urban China. *Kobe University Economic Review*, 54(1): 25-34.
- DEHEJIA, R.H. and WAHBA, S. (1999). Causal effects in non-experimental studies: reevaluation of the evaluation of training programs. *Journal of the American Statistical Association*, 94: 1053-1062.
- DEHEJIA, R.H. and WAHBA, S. (2001). Propensity score-matching methods for non-experimental causal studies. *The Review of Economics and Statistics*, 84(1): 151-161.
- DJURDJEVIC, D. and RADYAKIN, S. (2005). *Decomposition of the gender wage gap using matching: an application for Switzerland*. Darmstadt Discussion Paper No. 155.
- ERMISCH, J.F., and WRIGHT, R.E. (1993). Wage offers and full-time and part-time employment by British women. *The Journal of Human Resources*, 25(1): 111-133.
- GRILLI, L., and RAMPICHINI, C. (2011). Propensity scores for the estimation of average treatment effects in observational studies. Training Sessions on Causal Inference, Bristol on 28 June 2011.
- HARDOY, I. and SCHØNE, P. (2006). The part-time wage gap in Norway: how large is it really? *British Journal of Industrial Relations*, 44(2): 263-282.
- HECKMAN, J.J., ICHIMURA, H., SMITH, J. and TODD, P. (1998). Characterizing selection bias using experimental data. *Econometrica*, 66(5): 1017-1098.

- HIRSCH, B. T. (2004). *Why do part-time workers earn less? The role of worker and skills*. Institute for the Study of Labour (IZA) Discussion Paper No. 1261.
- HU, Y. and TIJDENS, K. (2003). *Choices for part-time jobs and the impacts on the wage differentials: a comparative study for Great Britain and the Netherlands*. Integrated Research Infrastructure in the Socio-Economic Sciences (IRSS) Working Paper No. 2003-05.
- JANN, B. (2008). The Blinder–Oaxaca decomposition for linear regression models. *The Stata Journal*, 8(4): 453–479.
- KHITARISHVILI, T. (2013). *Evaluating the gender wage gap in Georgia, 2004 – 2011*. The Levy Economics Institute Working Paper No. 768.
- KOCH, S.F (2013). Understanding counterfactuals and the treatment concept. EKT 816: Applied Microeconometrics Lecture Notes, University of Pretoria, Pretoria, September 2013.
- MINCER, J and POLACHEK S.W. (1974). Earnings of women. *Journal of Political Economy*, 82(1): S76-S108.
- MINCER, J. (1962). On-the-job training costs, returns, and some implications. *Journal of Political Economy*, 70(5): S50-S79.
- MULLER, C. (2009). *Trends in the gender wage gap and gender discrimination among part-time and full-time workers in post-apartheid South Africa*. University of KwaZulu Natal Working Paper, No. 124.
- NANNESON, F. (2011). Gender and income in Bolivia- using matching to decompose income. Seminar, Department of Economics, University of Copenhagen in the Spring of 2011.
- NICHOLS, A (2008). Erratum and discussion of propensity-score reweighting. *The Stata Journal*, 8 (4): 532–539.
- NOPO, H. (2004). *Matching as a tool to decompose wage gaps*. IZA Discussion Paper No. 981.
- OAXACA, R.L. (1973). Male-female wage differentials in urban labor markets. *International Economic Review*, 14 (3): 693-709.
- OAXACA, R.L., and NEUMAN, S. (2004). Wage decompositions with selectivity-corrected wage equations: a methodological note. *Journal of Economic Inequality*, 2(1): 3-10.
- OECD EMPLOYMENT DATABASE (2013). Gender pay gaps for full-time workers and earnings differentials by educational attainment. Available at:  
<http://www.oecd.org/els/soc/LMF1.5%20Gender%20pay%20gaps%20for%20full%20time%20workers%20-%20updated%20290712.pdf> [Accessed 10 November 2013].

- OWEN, J. D. (1978). Why part-time workers tend to be in low-wage jobs. *Monthly Labour Review*, 101(6): 11-14.
- POLACHEK, S.W. (1981). Occupational self-selection: a human capital approach to sex differences in occupation structure. *Review of Economics and Statistics*, 63(1): 60-69.
- POSEL, D. and MULLER, C. (2008). Is there evidence of a wage penalty to female part-time employment in South Africa? *The South African Journal of Economics*, 76(3): 466 - 479.
- POSNER, M. A., and ASH, A. S. Comparing weighting methods in propensity score analysis. Available at: [http://www.stat.columbia.edu/~gelman/stuff\\_for\\_blog/posner.pdf](http://www.stat.columbia.edu/~gelman/stuff_for_blog/posner.pdf) [Accessed 4 October 2013].
- PRATAP, S. and QUINTIN, E. (2006). Are labor markets segmented in developing countries? A semi-parametric approach. *European Economic Review*, 50(7): 1817-1841.
- RODGERS, J. R. (2004). Hourly wages of full-time and part-time employees in Australia. *Australian Journal of Labour Economics*, 7(1): 215-238.
- ROSENBAUM P.R., and RUBIN, D.B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70 (1): 41-55.
- SPRINGEL, K. (2011). Empirical assessment of the gender wage gap: an application of East Germany during transition (1990-1994). MA Dissertation. Central European University.
- STATA CORP (2013). Stata treatment effects reference manual: potential outcomes / counterfactual outcomes. Stata Release 13. Statistical Software. College Station, Tx: Statacorp Lp.
- YASIN, G, CHAUDHRY, I.S and AFZAL, S. (2010). The determinants of gender wage discrimination in Pakistan: econometric evidence from Punjab province. *Asian Social Science*, 6(11): 239-255.