

ERASMUS UNIVERSITY ROTTERDAM

Erasmus School of Economics

Bachelor Thesis (International Bachelor Economics & Business Economics [IBEB])

**Does the Broad Based Black Economic Empowerment (BBBEE) Act in South Africa Truly
Empower People?**

Rado Damianov 536692

Supervisor: A.I. Figueiredo

Second assessor: A. Baiardi

Date final version: 14 July 2022

**The views stated in this thesis are those of the author and not necessarily those of the supervisor,
second assessor, Erasmus School of Economics or Erasmus University Rotterdam.**

Abstract:

South Africa is a country that has a very complicated history due to the apartheid regime that for over 40 years discriminated against Black/African, Indian, Asian, and Coloured population groups. In order to mend the consequences of this regime, many policies and laws such as the Broad-Based Black Economic Empowerment (BBBEE) Act (an example of an Active Labour Market Policy) were implemented after the collapse of apartheid. Using an empirical analysis of a difference-in-difference model, this study aimed to explore whether the BBBEE brought about to the previously disadvantaged population groups in South Africa a significant change in the unemployment rates and in their access to unemployment benefits (UIF). Data were collected from the Labour Force Survey (LFS) for the period 2000 to 2010. It was found that in the post BBBEE inception period previously disadvantaged individuals were on average 3.9% less likely to be unemployed but their access to the UIF has remained limited. It was concluded that the BBBEE was effective in creating job opportunities but did not have a significant impact on expanding the accessibility of the UIF to those who were previously disadvantaged. Further research should examine whether these findings remain consistent in more recent years, especially with more detailed data regarding the UIF.

1. Introduction:

Unemployment insurance is a common social benefit offered in many countries worldwide. In January 2022 alone, \$2.49 billion unemployment funds were paid in the United States (Statista, 2022). This benefit is particularly valuable in developing countries, where it is harder for workers to find jobs and thus they require some form of financial aid to rely on while looking for employment. Among the countries with the highest unemployment rates, South Africa had a broad unemployment rate of 41% in 2004 (Klasen & Woolard, 2008). One of the oldest social welfare programs in the country is the Unemployment Insurance Fund (UIF), first introduced in 1946 (Lund, 1993). The purpose of this program is to provide financial aid to workers if they get retrenched from their job, while actively seeking new employment (SARS, 2022).

The South African government prides itself with the UIF and considers it a benefit which helps citizens find employment (South African Government, 2022). Historically, the implementation of this benefit has been controversial as during the apartheid regime, non-white workers were not eligible. Once the apartheid regime collapsed in 1994, this restriction was dropped and the eligibility requirements changed to address the needs of the previously disadvantaged communities. Furthermore, in order to mend the damages that apartheid left on the South African society, and particularly on the individuals who had been discriminated against (non-white individuals), in 2003 the Broad-Based Black Economic Empowerment (BBBEE) Act was implemented. The aim of this policy was to incorporate black people (defined as people who are African, Indian, Asian, or Coloured) into the South African economy by providing them with better prospects for managerial and higher-order jobs in order to increase their representation in the workforce and in ownerships, and to minimize the inequality of opportunities based on an individual's population group (Government Gazette, 2004). This type of policy is relatable to the more well-known Active Labour Market Policies (ALMPs), which specifically aims at decreasing unemployment in a country and increasing the labour force simultaneously. These policies are more common within the Organisation of Economic Co-operation & Development (OECD) countries, however are gradually being implemented into developing countries such as South Africa.

Thus far unemployment benefits have been primarily investigated in the context of the US (Anderson & Meyer, 1997; Holmlund, 1998). In South Africa, most of the research on the

UIF has utilised a descriptive exploration of the available data (Bhorat et. al., 2013), and less attention has been given to conducting empirical analysis that can deduce potential causality. To date, most of the literature on the BBBEE outlines a theoretical or political analysis of the act (Andreasson, 2006; Tangri & Southall, 2008). The present study is one of the first to bring together the political and economic aspects of the transformation in South Africa. These include the consequences of the collapse of the apartheid regime, unemployment, segregation, and an economic analysis of the effectiveness of a post-apartheid policy. Furthermore, as the BBBEE is relatable to ALMPs, the theoretical contributions put forward encompass a unique perspective on the latter with a focus on a developing country. Most previous research analyses the efficiency of these types of policies for developed or OECD countries such as Sweden (Calmfors et. al, 2002), or Germany (Lechner & Wunsch, 2009). The effectiveness of ALMPs, though generally high, depends on the particular type and context of implementation (Kluve, 2016).

In order to examine whether the BBBEE was successful in creating job opportunities for previously discriminated population groups in South Africa, I study the impact of this policy on the probability of being unemployed and on the use of unemployment benefits since the implementation of the BBBEE. I investigate the policy effect on an individual being unemployed based on their population group, which will reveal how successful the BBBEE policy was in achieving the aim of providing job opportunities for people of colour. In addition to the unemployment rate, I use the related UIF financial benefit to test the effect that an individual of a certain population group is likely to use this benefit. More specifically, I apply a Differences-in-Differences (DiD) model in order to address the above question. In order to use this method, one requires a pre- and post-period, and a treatment and a control group. Since the policy was implemented in 2003, the pre-period consists of data from 2000 to 2002, and the post period includes data from 2003 to 2010. The treatment group comprises individuals who were discriminated against during apartheid, since the BBBEE aims to try and create more job opportunities for these previously discriminated individuals. Non-discriminated individuals make up the control group. Data on all of these variables are collected from the Labour Force Survey (LFS), obtainable from the University of Cape Town data portal. Furthermore, age, education status, and gender are controlled for within the models. Robustness checks are conducted on the assumptions of a DiD model, and checks are run to ascertain if the conclusions hold when using different definitions for the term ‘unemployed’.

The model analyzing unemployment indicates that there is on average a 3.9% decrease in unemployment rates for previously discriminated population groups after the implementation of the BBBEE, and this effect is significant. This conclusion holds when using different measures of unemployment, with a consistent decrease shown. To test for heterogeneous effects, the sample is split into high school and university graduates, revealing that the BBBEE was more beneficial for university graduates. In the UIF model, the results indicate that previously discriminated population groups are on average 0.9% more likely to claim the UIF after the implementation of the policy, however this effect is not significant. The Parallel Trends Assumption (PTA) holds for the unemployment model, but cannot be tested for the UIF model due to missing data in the pre-period.

As a whole, these results suggest that the BBBEE has been successful in lowering unemployment rates for previously discriminated population groups. However, regarding the UIF benefit, a more thorough empirical analysis should be done, both by future researchers and by the South African government. On the one hand, a very small proportion of respondents reported using this benefit, and on the other hand it transpired that there are certain issues regarding data collection on this benefit.

The rest of the paper is structured as follows. The next section outlines the theoretical underpinnings and past research on this topic, followed by a section which gives further detail on the context, objectives and implementation of the BBBEE. Thereafter is a description of the data set, an analysis of the descriptive statistics, and a description of the empirical model being used. Following that is the results section, then an outline of the robustness checks. Subsequent sections are the discussion of the results, limitations, future recommendations, and implications. The conclusion summarizes the key findings and observations of the paper.

2. **Literature review:**

This section summarises previous theoretical and empirical literature relevant to this research, namely unemployment rates and unemployment benefits, with specific reference to the South African context. Following this is an examination of ALMPs, since the BBBEE is an example of one. The section is concluded with a review of literature on the topic of the BBBEE.

Theory suggests that generous unemployment insurance results in larger and persevering unemployment levels, and thus certain governments aim to create policies that decrease the

unemployment benefits (Holmlund, 1998). Similar conclusions are reached by Hagedorn et. al. (2013), who argued that increasing unemployment benefits (in terms of length, not quantity) ultimately decrease employment and job opportunities, while increasing unemployment. Contrasting empirical research on unemployment benefits in the US has concluded that a higher benefit increases the job-finding rate for an individual seeking employment (Anderson & Meyer, 1997).

Some models have predicted that an individual is more likely to rely on social benefits if the duration is longer, and the benefit is larger in monetary value (Riphahn, 2001). A potential problem is that certain individuals do not claim their social benefits, as was seen in a case study conducted in Germany (Riphahn, 2001). Individuals are more prone to use a social benefit if they are automatically enrolled for it (Currie, 2004), however with certain social benefits such as the UIF individuals are not automatically enrolled. Research conducted specifically on unemployment in South Africa concludes that unemployed individuals who do not receive social benefits tend to stay in households with individuals who can support them, such as family, which in turn increases household poverty levels and decreases active job-seeking (Klasen & Woolard, 2008). In addition, claimants who are female, young, and deemed poorer have the lowest potential claim days when claiming (Bhorat et. al., 2013), though this trend has not been comparatively investigated for specific population groups. This suggests that the interplay between employment opportunities and unemployment benefits are multidimensional.

One way of addressing unemployment in a country is by implementing ALMPs. ALMPs are quite popular within the EU and OECD countries, whereas Bulgaria, France, Estonia, Portugal, and Denmark have all recently begun implementing certain types of ALMPs (European Commission, 2017). The main aim of ALMPs is to make the labour market more efficient by focusing on reducing the unemployment rate and simultaneously creating a larger labour force. (Calmfors, 1994). This can be done in one of three ways: matching, training, and job creation. Once it has been established which specific type of ALMP is to be implemented, there are two methods in evaluating its efficiency. The first method compares an individual's employment outcomes to an individual who did not participate in the policy, while the second method measures the net effect of employment after taking into account factors such as subsidies (Martin & Grubb, 2001). A theoretical cost-benefit analysis conducted by Kahn (2011), specifies an interesting trade off when determining whether to make the labour market more flexible or not.

Making the labour market more flexible allows for new entrants such as women or immigrants, however, this could threaten the economic position of certain incumbents in the labour force.

According to research conducted in Sweden, ALMPs can play an important role in job creation, however, less so for matching an individual to a job, whereas training programmes do not increase an individual's likelihood of obtaining a job (Calmfors et. al. 2002). Similar research conducted in Latin America and the Caribbeans (LAC), suggests two important outcomes of ALMPs. Firstly, unemployed females benefit more and secondly, LAC countries accomplish more impactful ALMPs when their economies are strong and the unemployment rate is low (Kluge, 2016). Lechner and Wunsch (2009) claim the exact opposite - that these programs are more effective when unemployment is increasing. An alternative conclusion by Card et al. (2010) who has rather focused on the efficiency of analysing an ALMP empirically is that the outcome variable chosen as unit of measurement is important and can impact the overall results. The overarching view based on empirical research is that ALMPs are effective in matching, not as effective in job creation, and in terms of training - are more effective in the long-run than the short-run (Kluge, 2016).

In South Africa, certain policies implemented by the government have the specific aim to decrease unemployment, such as the BBBEE which in its essence may be considered an ALMP. The BBBEE Act has been researched mainly from a political and ideological perspective (Andreasson, 2006; Tangri & Southall, 2008) but less so from an economic and empirical angle. It has been argued that the post-apartheid transformation has not brought about a sufficient positive significant impact on the South African society in terms of education, employment, and wages, and that due to economic constraints, the BBBEE has had a very limited impact on the nation (Ponte et. al., 2007). However, between 2001 and 2007, there was a significant increase in Black individuals, particularly Black females obtaining managerial position jobs, along with a decrease in White representation (Horwitz & Jain, 2011). Overall there are contrasting views on whom the BBBEE benefits, as some authors claim that the policy only aims to improve the lives of previously discriminated individuals (Southall, 2004). Others conclude that indirectly it is beneficial not only to Black individuals but to other groups as well, such as employees involved in BBBEE deals between companies (Patel & Graham, 2012).

The present study has the following contributions. It strengthens the literature on ALMPs, and is particularly useful since most of the empirical research conducted on the topic focuses on

OECD or EU countries and there is less literature on how effective these types of labour policies are in African or developing countries. This study is also contributing to the economic analysis of the role that the BBBEE Act has had on the South African society. Some of the research conducted so far has utilised a general descriptive analysis of collected data and primarily examined trends and statistics based on certain factors and demographics. However, this study applies an econometric model, DiD, in order to try and address potential causality. Moreover, this paper is one of the first to conjointly address the UIF, unemployment levels across population groups, the BBBEE, and ALMPs all in one study. Overall, the exploration undertaken is relevant from a labor, historical, social, political, and policy making perspective.

Taking all of the above into consideration, I conducted this study with the aim to explore whether the BBBEE policy brought about to previously disadvantaged population groups in South Africa a significant change in the unemployment rates and their access to unemployment benefits. I hypothesize that over the 10-year period since the implementation of the BBBEE: i) there will be a significant difference in the unemployment rate of the previously disadvantaged population groups compared to the non-discriminated population groups, and ii) there will be a significant difference in the access to UIF benefits of the previously disadvantaged population groups compared to the non-discriminated population groups.

3. Institutional Background of the BBBEE:

This section highlights the specificities of the BBBEE, namely looking at the context as to why this policy was implemented, followed by a brief description of the main objectives and aims of the policy, and lastly presenting a concise outline of the implementation process.

3.1 Context

During the apartheid regime, non-white population groups had very limited access to the South African economy, in terms of job opportunities, ownership of capital, property and other assets, which resulted in substantial income inequality within the nation and between population groups. Due to these aforementioned inefficiencies, the South African economy is not in an optimal position. The Reconstruction and Development Programme (RDP) of 1997 stipulated an end to discriminatory acts and aimed to protect all South African citizens. Other acts such as the 1997 Green Paper on Public Procurement Reform were not specific enough in their objectives and aims, and thus certain individuals found loopholes around these reforms. This ultimately led

to the need of a more specific and holistic reform to be implemented, hence the creation of the BBBEE Act in 2003.

3.2 Objectives

The BBBEE Act aimed to be more specific and purposeful in promoting a democratic society, by eliminating discriminatory acts in the labour force, economy, and overall society. The Act has seven specific objectives, which it aims to achieve, such as addressing issues regarding diversity in the workforce, ownership of assets and property by all population groups, creating more opportunities for underskilled individuals and workers enabling them to successfully learn the required skills they need for obtaining jobs and performing them efficiently. Other aims include: strengthening of women's involvement in managerial positions, creating investment and finance programs so that Black individuals can sustainably contribute to the South African economy, and lastly providing townships and communities with the agricultural means they need to live healthily and sustainably. The Act therefore focuses on the promotion of a democratic and egalitarian society. Thus, the BBBEE Act has traits of both training and job creation type ALMPs.

3.3 Implementation

In order to achieve the above objectives, the Act introduced three types of transformation interventions: controlling ownership of assets and property by the government via regular monitoring, enforcement of human resources departments in businesses and organisations in order to create and develop skills, and lastly, more specific policies aimed at socioeconomic development. In order to measure whether organisations and individuals are achieving these interventions, a BBBEE scorecard was created in 2005, which measures an organization's compliance with the BBBEE rules and regulations. There are seven sections within the scorecard, one for each objective of the act, and within each section an organization is scored on how successfully they are implementing the objective. The overall score obtained is important because organisations with a low score become ineligible for subsidies from the government and/or entering into partnerships. Thus, it is important for companies to obtain a high BBBEE score, as this provides for them more business and growth opportunities. The first method proposed by Martin and Grubb (2001) for evaluating the efficiency of an ALMP, which compares an individual participating in treatment or policy to a non-participating one, is more appropriate to be used in this context.

4. Data:

In this section I describe the data source, the data collection process, and how I pool the data to take into account certain eligibility requirements. Following this, I define the main variables of interest, how the treatment and control groups were created, and lastly, I analyse the descriptive statistics for the data.

4.1 Data Sources and Sample Selection:

Primary data were originally generated by the Labour Force Survey (LFS) and were accessible from the DataFirst portal, owned by the University of Cape Town (UCT), in South Africa. The LFS consists of a thorough questionnaire administered by an interviewer with a South African citizen, where questions on topics such as death, personal life, and work life are asked. Most of the data are extracted from the section of the survey based on the individual's work life. Since the BBBEE Act was implemented in 2003, repeated cross-sectional data were collected for the period 2000 to 2010, thus spanning over the course of a decade. Between 2000 and 2007, the LFS was conducted on a semi-annual basis in March and September, but from 2008 it became a quarterly conducted survey. In order to stay consistent throughout the data collection process, for the period 2008 to 2010, I collect data only from the surveys from the first and third quarters, which represent March and September, respectively. By using data from two surveys per year, the complete data set is composed from 20 surveys between the years 2000 and 2010.

I pool the data to only include individuals in the age group between 25 and 54 as only 11% of individuals between the ages of 15 to 24 are employed (Old Mutual, 2022), and this predominantly refers to low-income jobs. More so, the BBBEE encourages provision of opportunities for employment in managerial positions and individuals between 15 and 24 are less prone to receive such jobs. In order to qualify for the UIF, one must have had prior employment, while most individuals in this age category are likely to be working for the first time. For these reasons, I exclude individuals between the ages of 15 and 24 from the data sample. Similarly, I also exclude individuals between the ages of 55 and 64 from the sample as between these ages, individuals are more likely to start retiring and in South Africa a pension fund benefit can be claimed from the age of 55 (Pension Bee, 2022).

I only include individuals who have obtained at least a high school diploma or university degree. An important emphasis of the BBBEE is to provide higher-position jobs to individuals

who had been discriminated against during apartheid. Thus, university graduates were included as they are the most likely to meet the BBBEE eligibility criteria. High school graduates were retained in the sample so that a comparative analysis could be run to reveal whether the level of education is indeed an employment advantage in the application of the BBBEE.

Lastly, it is important to mention that the selection criteria of the age of 25 for inclusion in the data set is related to the level of education. Once an individual obtains a university degree at approximately age 21, I control for job employability in the first few years after finishing school. Once an individual starts working, their employer starts contributing to their UIF. If they are retrenched, they become eligible to claim their UIF based on the duration they worked.

The sample therefore consists of both male and female respondents between the age of 25 and 54, who have obtained at least a high school diploma or university degree. After filtering the data for the aforementioned requirements, the final data set consists of 67 373 observations for the 10-year period. To keep the data balanced, individuals who answered ‘not applicable’ for employment status were removed from the sample, leaving 56,287 observations for the first hypothesis. For the second hypothesis, only unemployed individuals were left in the sample, totalling to 10,031 observations.

4.2 Treatment & Control Groups

During apartheid, non-white individuals were discriminated against and did not have equal opportunities to obtaining jobs, particularly higher order positions, such as, managerial positions. These previously discriminated individuals make up the treatment group, as the BBBEE policy aims at creating more job opportunities for them. Hence any individual who identifies as African or Black, Coloured, Indian or Asian is part of the treatment group, while any White individual is part of the control group.

4.3 Outcomes of Interest:

The following variables were extracted directly from the surveys without any additional adjustments needed: “year”, “official employment status”, “expanded employment status”, if the individual “has worked in the last 7 days”, whether the individual “claims the UIF in the last 7 days”, “population group”, “gender”, “age”, and “education”. Dummy variables for “official unemployment status”, “expanded unemployment status”, if the individual “has not worked in the last 7 days”, and “has access to the UIF”, were created. In the LFSs, the “official unemployment variable” captures those individuals who meet three criteria: i) have not had work

in the seven days prior to the interview; ii) are ready to start working seven days after the interview; and iii) have been actively seeking employment within a month prior to the interview (Statistics South Africa, 2006). The “expanded unemployment” variable captures criteria i) and ii) only. Dummy variables for “post”, “treated”, and “gender” were also created. Categorical variables were created for “education” and “population group”. “Official unemployment” and “expanded unemployment” equal 1 if an individual is unemployed, 0 otherwise. “Has not worked” equals 1 if the individual has not worked in the last 7 days, 0 otherwise. “Has access to UIF” equals 1 if the individual has access, 0 otherwise. In the dummy variable “gender”, a female is coded with 1 and a male with 0. “Post” equals 1 if the year is 2003 or later, 0 otherwise. “Treated” equals 1 if the individual is in the treatment group, 0 in the control group. “Population group” is equal to 1 if an individual is Black/African, 2 if the individual is Coloured, 3 if the individual is Indian/Asian, 4 if the individual is White. “Education” is a categorical variable which denotes 1 if the individual has a high school diploma, 2 if the individual has a university bachelor’s degree, 3 if the individual has a postgraduate, Honor’s, or Master’s degree, and 4 refers to “do not know”.

4.4 Summary Statistics:

4.4.1 Unemployment rate

When looking at the general descriptive statistics for the first hypothesis (Table 1), the average unemployment rate for the entire sample is approximately 17%, with 72% of the sample constituting the treatment group. Average unemployment rates are visually displayed in Figure 1. In 2000 it was just under 22%, and gradually decreased from 19% in 2002 to 15% in 2008. However, in 2008 the unemployment rate started increasing again, up to 18% in 2010 within the sample.

Furthermore, 55% of the sample are female, and the average age is approximately 38 years. Since education and population group are categorical variables, the average figures in Table 1 are not very indicative. In order to get some insight into the representation of the different categories, Figures 2 and 3 were compiled. Figure 2 indicates that nearly 60% of the sample are Black or African individuals, Coloured, Indian and Asian individuals make up approximately 13% of the sample, and the remainder (27%) are individuals who identify as White. There is a small category of 0.14% of individuals who identify as Other. These results are explicated by a cross tabulation, presented in Table 2. Figure 3 depicts a similar analysis but

looks at education status rather than population group. Just over 60% of the sample have obtained at least a high school diploma, and only around 10% have obtained a Master's or Honor's university degree.

Lastly, more detailed descriptive statistics based on an individual's population group can be seen in Appendix A. Nearly 20% of the Black and African respondents within the sample are unemployed, followed by Indian and Asian individuals (14%), then Coloured individuals, and lastly White individuals with an average unemployment rate of 12%. These figures reflect South Africa's segregatory history, where Black and African people found it more difficult to obtain jobs compared to White people. Average values based on population group are also given for an individual's age, treatment status, female proportion, and education level (Appendix A). In contrast to unemployment rates, White individuals have the highest average education status, while on average Black and African individuals have the lowest average education status, once again indicating that it is less likely for a Black or African individual to obtain a higher education degree.

4.4.2 UIF Claims

Regarding the second hypothesis, the dependent variable is the UIF claim rate. This subsample consists of individuals who are unemployed, and have answered that they either do or not claim the UIF. The descriptive statistical analysis indicates some concerning results regarding the UIF. On average, only 0.94% of unemployed individuals from the sample claim the UIF (Table 3). Further investigation of the trend of the UIF over the 10-year period, as shown in Figure 4, gives inconclusive results. The claim rate does increase after the implementation of the BBBEE Act in 2003, but in the next year it starts decreasing. Throughout the 10-year period, the claim rate does not change by more than 1%.

As seen in Table 3, 20% of the unemployed subsample identify as White while the remaining 80% fall under one of the three previously discriminated population groups, and 66% of the unemployed group are female. Since population group and education are categorical variables, once again it is more fruitful to analyze the data through a histogram (Figures 5 and 6). Figure 5 shows that 20% of the unemployed subsample are White individuals, while Coloured, Indian and Asian individuals represent a minority of less than 15% of the subsample. Figure 6 indicates that amongst the unemployed, over 60% have at least a high school diploma. However, there is a significant drop in tertiary education degrees amongst the unemployed subsample, with

less than 20% obtaining a Bachelor degree, and less than 10% obtaining a Masters or Honors degree.

Finally, it is also useful to take a look at the descriptive statistics per population group (Table 4; Appendix B). Black, African, and Coloured individuals have the lowest UIF claim rate on average of 1%, while Indian and Asian individuals have the highest rate at 4% on average. Of the unemployed subsample, Coloured individuals have the highest average education category, while Black and African individuals have the lowest average education status. In the unemployed subsample, the females comprise 80% of the White respondents, 70% of Indian respondents, 63% of the Black and African respondents and 60% of the Coloured respondents.

5. Empirical framework:

This section explains the empirical method used to investigate the two hypotheses, namely the DiD method which requires a pre- and post-period, and a treatment and control group. This section concludes with a discussion of the robustness checks that will be conducted, namely a parallel trends assumption check and operationalization of the unemployment definition.

The BBBEE was implemented in 2003, thus making the period from 2000 to 2002 the pre-treatment period, and the treatment period being from 2003 to 2010. Since the BBBEE aims to aid Black individuals, they constitute the treatment group, while White individuals constitute the control group. I control for certain characteristics such as gender, age, and education. Gender is a dummy variable, age is a continuous variable, while education is a categorical variable. A DiD approach is suitable, with the inclusion of a pre- and post-period, as well as a treatment and control group as explained above. Furthermore, treatment is determined at an aggregate level since the BBBEE is implemented at a governmental level. Therefore, I end up with two regression models of the following form, where equation (1) states that:

$$Unemployment_{it} = \beta_0 + \beta_1 Post_t + \beta_2 Treated_i + \beta_3 Post_t * Treated_i + \beta_4 Gender_i + \beta_5 Age_i + \beta_6 Education_i + \varepsilon_{it} \quad (1)$$

where the dependent variable ***Unemployment_{it}*** is a dummy variable that equals 1 if individual *i* in year *t* is unemployed. ***Post_t*** is a dummy variable which takes a value 1 if the year is equal to or greater than 2003 and 0 otherwise, ***Treated_i*** is a dummy variable which takes on

value 1 if an individual identifies as being Black and 0 otherwise. $Gender_i$, Age_i , and $Education_i$ are control variables. The main coefficient of interest is β_3 , which measures the effect of the policy on the treatment group. Similarly, equation (2) states:

$$UIF_{it} = \beta_0 + \beta_1 Post_t + \beta_2 Treated_i + \beta_3 Post_t * Treated_i + \beta_4 Gender_i + \beta_5 Age_i + \beta_6 Education_i + \varepsilon_{it} \quad (2)$$

where UIF_{it} is a dummy variable which measures the probability of individual i in time period t claiming the UIF benefit. Similarly, as in model (1), the remaining variables in model (2) stay the same. Once again, the main coefficient of interest is β_3 , which measures the effect of the policy on the treatment group. These two equations will also be run for high school and university graduates, to test for heterogeneous effects.

When conducting a DiD analysis, there is one very important assumption which needs to hold in order for the results of the model to be viewed as reliable, this is known as the parallel trends assumption (PTA). It assumes that there can be observable and unobservable differences between the treatment and control groups, but any changes should affect both groups in the same way (Columbia, 2019). This assumption will be tested in the robustness check section. Furthermore, I will also run the respective model with different operational definitions for unemployment.

6. Results:

This section presents the results of the DiD models run, and is split into three subsections. In the first subsection, where the unemployment rate is used as the outcome variable, it is shown that subsequent to its implementation, the BBBEE decreased unemployment for previously discriminated individuals by 3.9% on average. In the second subsection where the same model is run but with the UIF claim rate as the outcome variable, it is revealed that the policy resulted in an average increase of 0.9% in the claim rate for previously discriminated individuals, however this effect is not significant. The last subsection investigates heterogeneous effects by running the models from section (6.1) and (6.2) for high school individuals and university graduates respectively. The results suggest that the policy had a stronger impact for university graduates compared to high school graduates. The results for the first two subsections can be found in Table 5, and for the third subsection - in Table 6.

6.1 Unemployment Rate

Model (1) in Table 5 measures the official unemployment status, where individuals either answered that they are employed or unemployed. The post period effect shows that after 2003, on average unemployment decreased by 0.6%, which is a very small proportion and furthermore the effect is not significant. The treatment effect indicates that an individual from a previously discriminated population group was on average 9.4% more likely to be unemployed compared to a White individual. At a glance, this figure might seem negligible, as some might interpret it to mean that the BBBEE was unsuccessful in increasing job opportunities for previously discriminated population groups. However, it should be taken into account that decades of discrimination cannot be diminished within such a short space of time. Hence, upon deeper reflection, this outcome does make sense. The main variable of interest in the model, the interaction term between the post period and the treatment group, is negative and significant. It indicates that on average, an individual from a previously discriminated population group is 3.9% less likely to be unemployed after the implementation of the BBBEE Act in 2003, relative to the control group. This result lends support to the first hypothesis. The rest of the model includes covariates, which indicate that female individuals are on average 1.7% more likely to be unemployed compared to males, while the older an individual is by 1 year, they are on average 0.7% less likely to be unemployed. Lastly, an individual with a higher education status is on average 2.3% less likely to be unemployed - a finding further explored in section 6.3. As a whole the first model suggests that the BBBEE was successful in decreasing the unemployment rates for previously discriminated population groups.

6.2 Unemployment Benefits (UIF)

Model (2) in Table 5 measures an unemployed individual's likelihood to have claimed the UIF in the last 7 days. There are two important points to emphasize. Firstly, only respondents who were recorded as being unemployed have been selected in the subsample for this model. Secondly, the formulation of the question asking about claiming the UIF within the last 7 days indicates that the claim rate is measured in the short-term, not the long-term. A discussion on the significance of these 7 days as a time frame follows in the discussion section, where this shall be further addressed. From the descriptive statistics in the data section, it was clear the average UIF

claim rate was low, approximately 1% of the unemployed sample have claimed the benefit in the last 7 days. South Africa offers many other social benefits to its citizens. In an endeavour to put this figure into context, I also scrutinize data on some of the other benefits and sources of income that an unemployed individual may rely upon. It could be the case that individuals rely on a different benefit besides the UIF, or they are not eligible to claim the UIF. Appendix C.1 examines the first possibility more closely. The results from these analyses suggest that it is indeed the case. There are more frequently used means that unemployed individuals rely upon for financial support rather than using the UIF. Approximately 78% of the unemployed sample are supported by someone in the same household as them, significantly less but still a substantial amount of nearly 16% of the unemployed sample are supported by individuals outside of the household. This indicates that a large portion of unemployed individuals do not actually rely on social benefits, but rather on friends and family whom they may or may not live with. An even smaller group rely on savings (9%) and old age funds (5%), while benefits such as the UIF (0.87%) and Charity (0.82%) are the least used sources of financial support.

Further findings in Model (2) indicate that since the implementation of the BBBEE, individuals are on average 1.1% less likely to claim the UIF, and previously discriminated population groups are on average 1.3% less likely to claim the UIF. Neither of these variables (post, treated) have a significant effect. Similar to Model (1) in section 6.1, the coefficient of interest is the interaction effect between the post period and the treated variables. The model suggests that on average 0.9% of the discriminated individuals are more likely to claim the UIF relative to the control group, however this effect is not significant. The covariates in model (2) are significant. On average, unemployed female workers are 1.7% less likely to claim the UIF compared to men. This is an interesting observation because it contrasts the outcome indicated by model (1), which stated that female individuals are on average more likely to be unemployed. If female individuals are more likely to be unemployed, then one would expect them to be more likely, rather than less likely to claim the UIF. One possible explanation for this finding is that female individuals may rely on other social benefits, such as being on maternity leave and relying on child care benefits instead. With reference to age, it transpired that the older an individual gets by 1 year, they are on average 0.1% more likely to claim the UIF, which perhaps

depicts a trend of a relatively higher, though not significant, reliance on government support with the increase of age. With reference to education, the results show that respondents with higher levels of education are on average 0.4% less likely to claim. Understandably, an individual with a higher education status is less likely to claim the UIF, because due to their education they are less likely to be unemployed.

6.3 Heterogeneous Effects

In this part of the results section the two models discussed in sections 6.1 and 6.2 are re-run, however this time by splitting the sample according to education status. I thus obtain two groups, a group of high school graduates, and a group of university graduates, leading to an additional four regression models being run. Thus, the heterogeneous effects based on education can also be addressed. The respective results can be seen in Table 6.

The sample for high school graduates is larger than for university graduates as seen in Table 6. Model (1a) in Table 6 indicates that a previously discriminated individual possessing a high school degree is on average 4.3% less likely to be unemployed after the implementation of the BBBEE relative to the control group. However, as Model (1b) in Table 6 shows, an individual with a university degree is on average 5.1% less likely to be unemployed after the BBBEE relative to the control group. Comparing the outcomes of these models, it is evident that the BBBEE had a stronger significant effect for university graduates compared to high school graduates. In terms of UIF claims, model (2a) in Table 6 indicates that previously discriminated individuals who are high school graduates are 16.7% more likely to claim the UIF relative to the control group. With respect to university graduates, model (2b) in Table 6 does not show any statistically significant effects, however it does indicate that these individuals are on average 0.5% less likely to claim the UIF after the BBBEE relative to the control group. To sum up, it seems that individuals with a university degree were more benefited by the BBBEE than high school graduates.

7. Robustness Checks:

This section starts with a visual inspection of the PTA, followed by an event study which confirms the conclusion of the visual inspection that the assumption holds. The second

subsection includes models using alternative operationalisations as the outcome variable, and the third subsection brings together all three unemployment models and compares them to each other. All the models tested are consistent in showing that the BBBEE reduced unemployment after its implementation for previously discriminated individuals, and the effect is significant in two of the three models.

7.1 Analysis of Parallel Trends Assumption

The main assumption when doing a DiD model is the PTA, and in the first part of this robustness section I will test to see whether this assumption holds for model (1) from Table 5. The way this is done is via a visual inspection of the data (Figure 7) and an event study (Table 8). More specifically, for the PTA to hold, the differences between the treatment and control groups in the respective outcome variables of each of the models (unemployment in model 1 and UIF in model 2) should remain the same prior to treatment, that is, before 2003. Upon visual inspection of Figure 7, it is clear that this is indeed the case. The treatment and control groups follow a parallel trend between 2000 and 2003, thus indicating that visually the PTA does hold for model (1) in Table 5. In order to confirm the results from the visual inspection, an events study is conducted, with results presented in Table 8. In order for the PTA to hold, if the policy was hypothetically implemented one year prior to 2003 (in 2002), this lag should not be significant because if it were significant this would suggest that the differences between treatment and control were not parallel already before treatment began. The results from Table 8 show that moving the policy one year back ($t - 1$) is not significant, which suggests that the trends pre-treatment are parallel, and the assumption holds for model (1) in Table 5.

However, when testing the PTA for model (2), some problems arise. In order to test for the PTA, one requires data from at least two time periods, however data on UIF claims for 2001 and 2002 is missing (Figure 8), which inevitably means that the PTA cannot be tested for model (2) in Table 5. This is just one limitation of the UIF data, a more extensive discussion of other limitations follows in the next section. Due to the fact that the PTA cannot be tested for model (2), one should be cautious of the outcomes that this model produces in Table 5.

7.2 Alternative definitions of Unemployment

In the second part of the robustness section, I further analyse the outcomes of model (1), which tests the first hypothesis of this paper, by using alternative definitions for unemployed workers. Models (1c) and (1d) in Table 7 indicate the results of these alternative definitions for

the unemployment rate. Models (1c) and (1d) differ mainly in the fact that model (1c) incorporates only the first (i) criterion of the official unemployment definition, (stating that an individual has not worked in the past seven days), while model (1d) accounts for the first two criteria (i and ii), but not the third criterion (iii) (stating that an individual has actively been seeking work one month prior to the interview).

In both models in Table 7, the post period has a significant impact on the unemployment rate, however the sign of the impact is different in each of the two. In model (1c), an individual is on average 7.1% more likely to not have work in the last 7 days, while an individual is on average 5.2% less likely to be unemployed in model (1d). In terms of the treatment outcome, both models indicate a positive and significant effect on unemployment, with the average increasing likelihood of being unemployed varies from 5.6% (Model 1d) to 6.3% (Model 1c). The interaction between treatment and the post variables is significant in model (1c), but not in model (1d). Model (1c) indicates that a previously discriminated individual is on average 6.0% more likely to have worked in the last 7 days prior to the interview.

7.3 Bringing it Together

Taking all of this into account, I now compare these outcomes with the outcomes from model (1) in Table 5. The post period consistently decreases the likelihood of being unemployed in model (1d), however increases the likelihood of not working in model (1c). The impact is greater in model (1c) than in model (1d), with an average increase of 7.1% in model (1c) and an average decrease of 5.2% in model (1d). The effect of the treatment variable remains consistent across the three models indicating that previously discriminated population groups are on average more likely to be unemployed than the control group. The magnitude of this effect is on average 9.4% in model (1), 6.3% in model (1c), and 5.6% in model (1d). Consistencies can also be seen in the interaction between the post period and the treatment status. All three models [(1), (1c) and (1d)] indicate a decreasing effect on unemployment levels. The effect is not significant in model (1d), but is significant in both models (1) and (1c).

As a whole, it is evident that the BBEE had a greater impact in model (1c) compared to model (1), as on average the unemployment rate drops by 6% for previously discriminated races in model (1c), but by 3.9% on average in model (1). Female individuals are consistently more likely to be unemployed compared to men, while it seems the magnitude is stronger in models (1c) and (1d) than in model (1). Furthermore, age has a consistently negative impact on the

unemployment rate, and there is a very small variance of 0.1% between models (1), (1c), and (1d). Lastly, education shows a negative impact on unemployment, showing a greater impact of 3% in model (1c), and 1.6% in model (1d). Education is significant in models (1c) and (1d), but is not significant in the official unemployment definition (model 1).

Robustness checks for Model (2) in Table 5, with UIF as the dependent variable, are not feasible for two main reasons. Firstly, since the PTA cannot be tested, running any sort of robustness check would not be reliable. Secondly, even if the PTA did hold, the LFS data contain only one specific question on the UIF which makes it impossible to conduct the same comparative analyses as those in models (1), (1c) and (1d). One possible solution, which is further elaborated on in the next section, is to define the claim rate not only in the last 7 days, but with a longer time frame: for example if an individual has claimed the UIF in the last 3 months or the last 6 months. If data on this existed, then a robustness check on model (2) would be feasible.

8. Discussion:

In this section, I present a coherent account of the study, by confirming or rejecting the hypotheses discussed in the theoretical framework, interpreting the results from earlier, and finishing with a discussion on certain limitations and recommendations for further research.

8.1 Unemployment Rate

To recap, the first hypothesis stating that there will be a significant difference in the unemployment rate of the previously disadvantaged population groups compared to the non-discriminated population groups for the period 2000 to 2010 was confirmed. Figure 7 depicts that the average unemployment rate of the treatment group does decrease after 2003. As indicated in the results for model (1) in Table 5, there was a significant interaction effect between the treatment and the post variables. Specifically, the coefficient of the interaction indicates that after 2003, previously discriminated individuals were on average 3.9% less likely to be unemployed. It should be noted that in terms of magnitude, this percentage is rather low. This result appears aligned with the conclusions reached by Ponte et. al. (2007), who find that the BBBEE has had a limited impact on the South African society and economy, however is in line with research conducted in Sweden which concluded that ALMPs are effective in creating job opportunities (Calmfors et. al. 2001). In addition, the present study revealed that although the

BBBEE places a significant emphasis on increasing the job opportunities for women, they are on average 1.7% more likely to be unemployed. This result is in contrast to the investigation of Horwitz and Jain (2011), which found a decrease in unemployment for female workers in South Africa. However, it is in line with Kluve's (2016) findings, which suggest that female workers are more affected by ALMPs. It should be mentioned that the data set does not include data post 2010. Therefore, it is possible that within the last decade there could have been changes in the magnitude of the coefficient and/or rate of employability of women. Thus, a recommendation for future research is to use an even longer time period, possibly from 2000 to 2020, or if possible even after 2020. In that way one can also investigate what effect the COVID pandemic has had on unemployment rates in South Africa, and whether or not the pandemic has nullified the effects that the BBBEE was able to create. Simultaneously one can also investigate the long-term implications of ALMPs, and the impact the global pandemic has had on these types of labour policies.

The two models, (1c) and (1d), presented in Table 7 tested the robustness of the conclusions reached in model (1). Using alternative operationalizations of the variable 'unemployed', the findings obtained across these three models are overall consistent. In particular, the interaction variable has a negative significant effect on the average unemployment rate in models (1) and (1c). In light of the PTA assumption being met and the satisfactory robustness checks, one can conclude that the BBBEE caused a significant decrease in the unemployment rate for previously discriminated population groups. This conclusion is in line with the views of Horwitz and Jain (2011), who concluded that there was an increase in Black employment between 2001 and 2007.

8.2 Unemployment Benefits (UIF)

The second hypothesis, stating that there will be a significant difference in the access to UIF benefits of the previously disadvantaged population groups compared to the non-discriminated groups, was not confirmed. There were a few reasons as to why this was the case. Upon conducting a descriptive statistics analysis, it was observed that the average UIF claim rate was low, on average merely around 1% of the unemployed sample seem to have claimed the UIF in the last 7 days. This was further confirmed by a frequency analysis presented in Appendix C1, which showed that if unemployed, individuals are much more likely to depend on individuals within the same household for financial support.

These results are in line with the conclusions reached in Klasen and Woolard (2008), that unemployed individuals rely on family for financial support and this in turn decreases their attempt at actively trying to find a new job. This view may account for the very low usage of UIF by the unemployed people. Although the results show that an individual from a previously discriminated population group is on average 0.9% more likely to claim the UIF subsequent to the implementation of the BBBEE in 2003, this effect is not significant. Hence, I cannot conclude that there was a significant difference in the UIF claim rate after the implementation of the BBBEE. Furthermore, due to certain limitations regarding the UIF data, the validity of model (2) could not be tested. More specifically, data on the UIF claim rate is missing from the Labour Force Surveys for 2001 and 2002, thus the PTA could not be tested for model (2) of table 5. The missing data and the low UIF claim rates are two reasons which give light as to why the exploration undertaken on this theme is very limited from an empirical perspective. With such a low claim rate, it is difficult to conclude any significant impact, and with missing data one cannot test the validity of the model.

8.3 Future research & Limitations

For future research, it would be advised to try and compile data on the UIF by rephrasing the UIF question by rather asking an unemployed individual whether or not they have claimed the UIF in the last 6 months, or if they have ever claimed the UIF. This proposition is in line with the conclusions reached by Card et. al. (2010), which emphasise the importance of the chosen outcome variable, as it can greatly impact the analysis process of an ALMP. In the present study, it transpired that with a poorly defined question to measure UIF claims, the analysis was somewhat limited.

Another limitation pertaining to the data on the UIF is that there were no questions in the LFS allowing to account for the finding that so few unemployed individuals claim the benefit. Thus, a recommendation for future research would be to add a supplementary question to the section in the LFS tapping into reasons for not claiming UIF. In instances when a respondent is unemployed and they do not claim UIF, a follow up question should be asked about the reasons for and implications of not using this source of income. This information would be very useful, as it can indicate to the Department of Employment and Labour in South Africa what the common obstacles are for claiming UIF and what appropriate measures could be implemented for overcoming them.

The implications of the present study are that it shows that the BBBEE has been successful in decreasing the unemployment of previously discriminated population groups. This in turn means that the South African government should be satisfied with their efforts and outcomes of the policy and should continue pursuing policies which aim to create a fair and equal society for all its citizens. Considering that the BBBEE had elements of different forms of ALMPs, it is important to continue finding ways to decrease the unemployment levels by implementing more ALMPs, with a particular focus on one of the three types of ALMPs. The unemployment rate difference between population groups may have dropped over the years since the BBBEE's implementation, however the next step is to find ways to decrease the overall unemployment rate, since it is still too high, compared to developed countries.

The consideration for expanding the accessibility of the UIF benefit so that it can be utilised by more people is even more relevant. The follow-up additional explorations on the finding that most of the unemployed people do not claim the UIF, revealed that other sources of financial support are more frequently relied on. Although the LFSs' data set does not tap into the reasons for the low utilisation of the UIF, it may be argued that unemployed people are either unaware of this benefit, do not know how to properly apply for it and respectively claim it, or are not eligible for it. It is proposed that questions on such reasons should be included in the future rounds of the survey. In addition, a re-examination of the UIF policies and legislature might be beneficial for the government, as from the current findings it is clear that up to 2010 this benefit is not being optimised. This could be done in many ways, for example, by re-analysing the eligibility criteria and how this benefit is promoted to make unemployed individuals aware of its existence, as well as by effectively communicating what necessary steps need to be taken in order to apply and claim the benefit.

9. Conclusion:

Upon the collapse of the apartheid regime in 1994 and the start of a new democratic nation in South Africa, many policies and laws were implemented in order to mend the ways of the past. One of these policies was the Broad-Based Black Economic Empowerment Act (BBBEE), an example of an ALMP, which was implemented in 2003.

This research was undertaken with the purpose to conduct an impact evaluation of the BBBEE and to reveal if it was successful in achieving its aims. By pursuing this aim, the study

highlights how effective ALMPs are in developing countries. Respondents from a previously discriminated population group are included in the treatment group, while White individuals make up the control group. The data set is for the period 2000 to 2010, in order to have a pre- and post-period since the Act was implemented in 2003. The econometric method used to test the research question is a DiD model.

The model was run several times, with a different dependent variable in order to effectively address each hypothesis and to run robustness checks. In the first model, the official unemployment status was the dependent variable, while in the second model the UIF claim rate was the dependent variable. The first model revealed that the BBBEE resulted in an average decrease of unemployment by 3.9% for the previously discriminated individuals relative to the control group. Furthermore, through investigating the heterogeneous effects by splitting the sample into high school and university graduates, it was found that university graduates were less likely to be unemployed by an average of 0.8%.

Regarding the second model, the effect was not significant, and had a magnitude of an average increase of 0.9% in UIF claim rate for previously discriminated individuals. Thus the first hypothesis was confirmed, however there was not enough evidence in order to also confirm the second hypothesis.

Certain limitations pertain to the UIF data, namely: insufficient data to run the PTA check, the wording of the question on the financial support in case of unemployment as well as lack of information on the reasons for not utilising the UIF. Thus for future research I suggest collecting more complete data on the UIF, particularly regarding the pre-period, and furthermore adding a question to the LFS that asks unemployed individuals why they do not claim the UIF.

Overall, there were two important findings that came out from this research. Firstly, it was confirmed there was a significant drop in unemployment for previously discriminated population groups, which suggests that the BBBEE was successful in its aims and indicates the potential efficiency of ALMPs in developing countries such as South Africa. Secondly, it was shown that the UIF is not among the prime sources of financial support for the unemployed. Thus, there is room for the South African government to look into ways to make the UIF benefit more accessible to individuals who are currently unemployed. Overall, the study provided empirical evidence which proves of the work being put in to mend the apartheid past of the country.

References:

- Anderson, P.M., & Meyer, B. D. (1997). Unemployment Insurance Takeup Rates and the After-Tax Value of Benefits. *The Quarterly Journal of Economics*, 112(3), 913 - 937.
- Andreasson, S. (2006). The African National Congress and its critics: 'Predatory liberalism', black empowerment and intra-alliance tensions in post-apartheid South Africa. *Democratization*, 13(02), 303-322.
- Bhorat, H., Goga, S., & Tseng, D. (2013). Unemployment Insurance in South Africa: A Descriptive Overview of Claimants and Claims. Development Policy Research Unit.
- Black Economic Empowerment. Wikipedia. Retrieved 1 July 2022 from [https://en.wikipedia.org/w/index.php?title=Black Economic Empowerment&oldid=1089911723](https://en.wikipedia.org/w/index.php?title=Black_Economic_Empowerment&oldid=1089911723)
- 4.
- Broad-Based Black Economic Empowerment Act (2003). Government Gazette, Vol. 463, No. 25899.
- Calmfors, L. (1994). Active Labour Market Policy and Unemployment - A Framework for the Analysis of Crucial Design Features. OECD Economic Studies No. 22.
- Calmfors, L., Forslund, A., & Hemstrom, M. (2002). Does active labour market policy work? Lessons from the Swedish experiences. Institute for International Economic Studies, Stockholm University. Seminar Paper No. 700.
- Card, D., Kluve, J., & Weber, A. (2010). Active Labour Market Policy Evaluations: A Meta Analysis. *The Economic Journal*, 120 (November), F452 - F477.
- Currie, J. (2004). The Take Up of Social Benefits. National Bureau of Economic Research.
- Data Portal. (2022). Retrieved 16 April 2022 from <https://www.datafirst.uct.ac.za/dataportal/index.php/catalog/central>
- Difference-in-differences (Did) and DDD models. (2022). Retrieved 4 June 2022, from <https://www.statista.com/new-in-stata/difference-in-differences-DID-DDD/>

Difference-in-difference estimation | Columbia Public Health (2019). Retrieved 4 June 2022, from <https://www.publichealth.columbia.edu/research/population-health-methods/difference-difference-estimation>

Employment and labor on unemployment insurance fund creating job opportunities | South African government. Retrieved 21 April 2022, from <https://www.gov.za/speeches/employment-and-labour-unemployment-insurance-fund-creating-job-opportunities-17-mar-2022>

European Commission (2017). European Semester Thematic Factsheet: Active Labour Market Policies. Retrieved on 4 July 2022, from https://ec.europa.eu/info/sites/default/files/european-semester_thematic-factsheet_active-labour-market-policies_en_0.pdf

Hagedorn, M., Karahan, F., Manovskii, I., & Mitman, K (2013). Unemployment Benefits and Unemployment in the Great Recession: The Role of Macro Effects. National Bureau of Economic Research.

Holmlund, B. (1998). Unemployment Insurance in Theory and Practice. *Scandinavian Journal of Economics*, 100(1), 113 - 141.

Horn, AJ. (2021). South Africa's Unemployment Insurance Fund Benefit Function: A Mathematical Critique. Cape Town: SALDRU, UCT. (SALDRU Working Paper Number 276).

Horwitz, F.M., & Jain, H. (2011). An assessment of employment equity and broad based black economic empowerment developments in South Africa. *Equality, Diversity and Inclusion: An International Journal*, 30(4), 297 - 317.

How to withdraw money from a pension fund | PensionBee. (2022). Retrieved April 24 2022, from <https://www.pensionbee.com/pensions-explained/pension-withdrawal/how-to-withdraw-money-from-a-pension-fund>

- Kahn, L.M. (2011). Labour Market Policy: A Comparative View on the Costs and Benefits of Labour Market Flexibility. *Journal of Policy Analysis and Management*, Vol. 31, No.1, 94 - 110.
- Kaseke, E. (2010). The role of social security in South Africa. *International Social Work*, 53(2), 159 - 168.
- Klasen, S. & Woolard, I. (2008). Surviving Unemployment Without State Support: Unemployment and Household Formation in South Africa. *Journal of African Economies*, 18(1), 1 - 51.
- Kluve, J. (2016). A review of the effectiveness of Active Labour Market Market Programmes with a focus on Latin America and the Caribbean. International Labour Office.
- Labour Force Survey September 2006 | Statistics South Africa Retrieved 1 July 2022 from <https://www.statssa.gov.za/publications/P0210/P0210September2006.pdf>
- Lechner, M., & Wunsch, C. (2009). Are Training Programs More Effective When Unemployment Is High? *Journal of Labour Economics*, vol. 27, no. 4.
- Lund, F. (1993). State Social Benefits in South Africa. *International Social Security Review*, 46(1), 5 - 25.
- Martin, J.P., & Grubb, D. (2001). What works and for whom: a review of OECD countries' experiences with active labour market policies. Working Paper, No. 2001:14, Institute for Labour Market Policy Evaluation (IFAU).
- McEwan, P.J. (2010). Empirical Research Methods in the Economics of Education. *International Encyclopedia of Education*: 187. Doi: 10.1016/B978-0-08-044894-7.01211-2
- Meth, C. (2011). Employer of Last Resort? South Africa's Expanded Public Works Programme (EPWP). A Southern Africa Labour and Development Research Unit Working Paper Number 58. Cape Town: SALDRU, University of Cape Town.

OECD 2022 | South Africa Education Retrieved 25 April 2022 from

https://www.oecd.org/education/education-at-a-glance/EAG2019_CN_ZAF.pdf

Patel, L., & Graham, L. (2012). How broad-based is broad-based black economic empowerment? *Development Southern Africa*, 29(2), 193-207.

Ponte, S., Roberts, S., & van Sittert, L. (2007). 'Black Economic Empowerment', *Business and the State in South Africa*. *Development and Change*, 38(5), 933 - 955.

Riphahn, R. T. (2001). Rational poverty or poor rationality? The take-up of social assistance benefits. *Review of Income and Wealth*, 47(3), 379 - 398.

SA's employment rate by age group | Infographic. (2022). Retrieved April 18 2022, from

<https://www.oldmutual.co.za/corporate/resource-hub/all-articles/infographic-SAs-employment-rate-by-age-group/>

Tangri, R., & Southall, R. (2008). The politics of black economic empowerment in South Africa. *Journal of Southern African Studies*, 34(3), 699-716.

Total monthly unemployment benefits paid U.S. 2022. (2022) Statista. Retrieved 22 April 2022

from <https://www.statista.com/statistics/284857/total-unemployment-benefits-paid-in-the-us/>

Unemployment Insurance Fund | South African Revenue Service. (2021a, February 4)

<https://www.sars.gov.za/types-of-tax/unemployment-insurance-fund/>

Woolridge, J. (2012). Difference-in-differences estimation. Michigan State University.

<https://ifs.org.uk/docs/wooldridge%20session%205.pdf>

Tables & Figures:

Table 1 Descriptive statistics of the data sample used for the first hypothesis for the period 2000 – 2010

Variable	Observations	Mean	Standard Deviation	Min	Max
Unemployed	56,287	0.17	0.37	0	1
Population group	56,287	2.01	1.32	1	5
Treatment	56,287	0.72	0.45	0	1
Female	56,287	0.55	0.50	0	1
Age	56,287	38.07	8.06	25	54
Education	56,287	1.61	0.91	1	4

Note: Unemployed, Treatment, and Female are dummy variables. Unemployed equals 1 if the individual is unemployed, 0 if they are employed. Treatment equals 1 if an individual is Black/African, Indian/Asian, or Coloured, and 0 if they are White. Female equals 1 if an individual is female, and 0 otherwise. Race and Education are categorical variables. Race is measured as follows: 1 equals a Black/African individual, 2 equals a Coloured individual, 3 equals an Indian/Asian individual, 4 equals a White individual, 5 equals Other. Education is measured as follows: 1 equals high school diploma, 2 equals university bachelors' diploma, 3 equals university honours/masters diploma, and 4 equals if an individual answered "Do not know". Age is a continuous variable measured in years.

Table 2 Average values (based on population group) of the data sample used for the first hypothesis for the period 2000 – 2010

Population group	Percentage of sample (%)	Unemployed (%)	Female (%)	Age (years)	Treated
Black/African	59.03	19.59	57.45	37.08	1
Coloured	8.99	13.14	52.55	38.71	1
Indian/Asian	4.21	13.99	46.51	37.53	1
White	27.62	12.21	50.19	40.06	0
Other	0.14	20.65	31.52	36.84	1

Note: The table gives the average values of certain indicators based on race category. The five race categories are indicated in the first column, and the indicators being measured are shown in the top row. Treated indicates whether this group is part of the treatment or control group, a 1 indicates treatment, a 0 indicates control group. The racial category "Other" is for any individuals who do not fall under one of the top four categories.

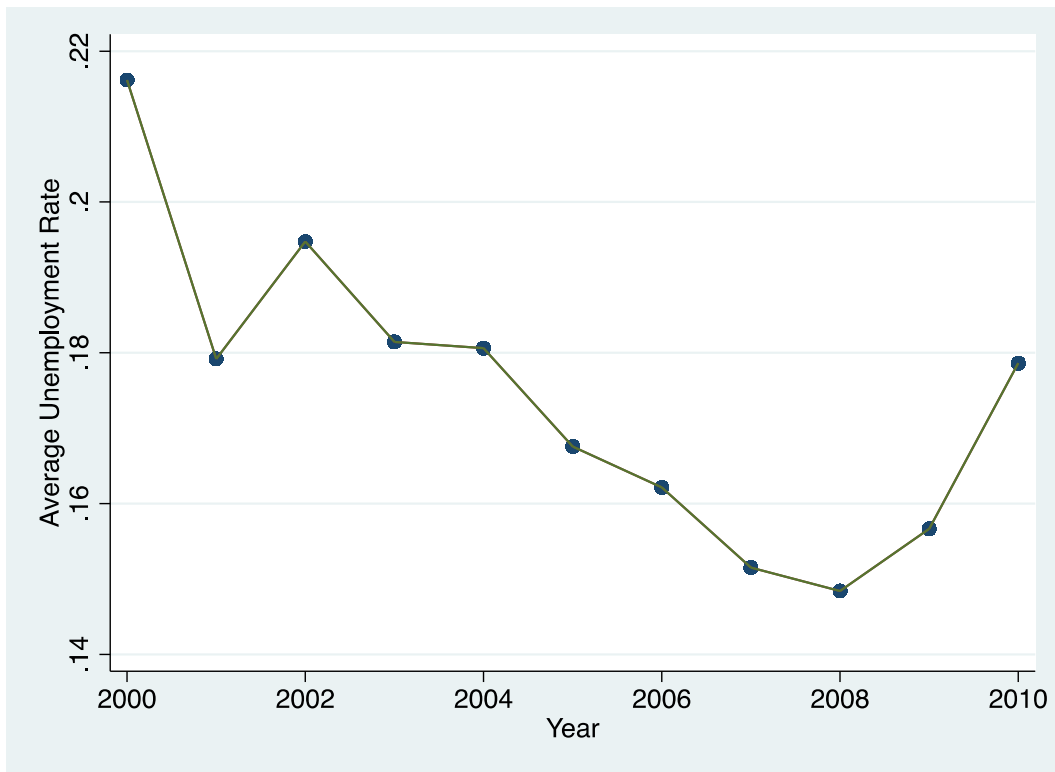


Figure 1 Unemployment levels for South African citizens for the period 2000 – 2010

Note: The year is on the x axis, and the unemployment rate on the y axis. The unemployment rate is measured between 0 and 1, thus the interval multiplied by 100 indicates the percentage of unemployed.

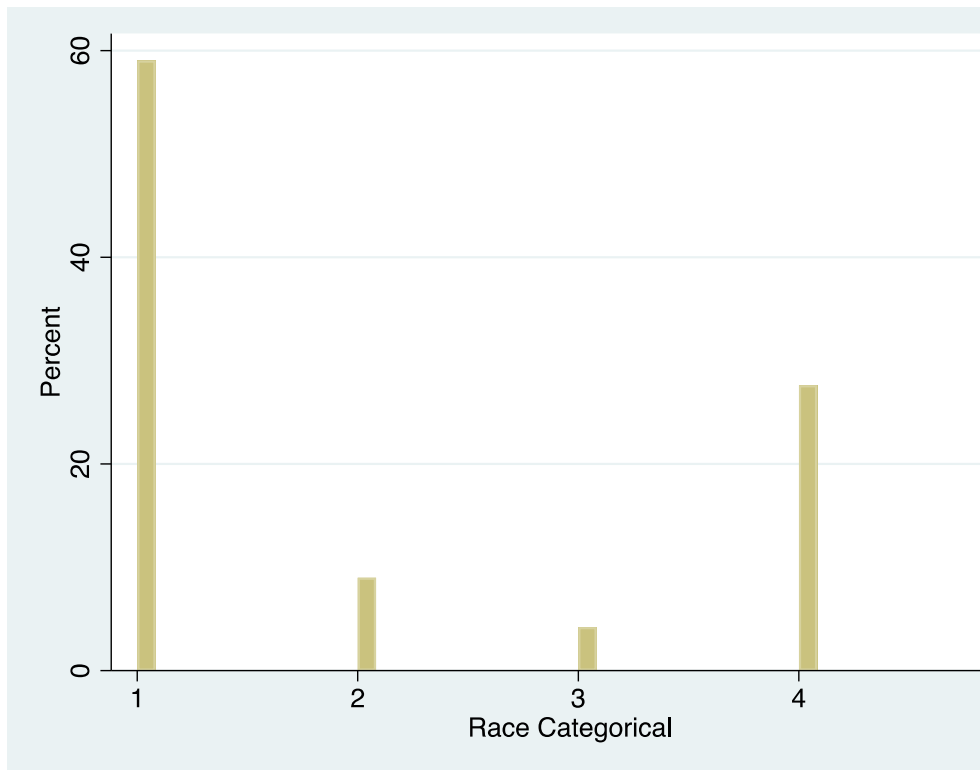


Figure 2 Percentage composition of individuals for the first hypothesis based on population group

Note: The percentage is on the y axis, the population group on the x axis. Column 1 indicates Black/African individuals, 2 indicates Coloured individuals, 3 indicates Indian/Asian individuals, and 4 indicates White individuals.

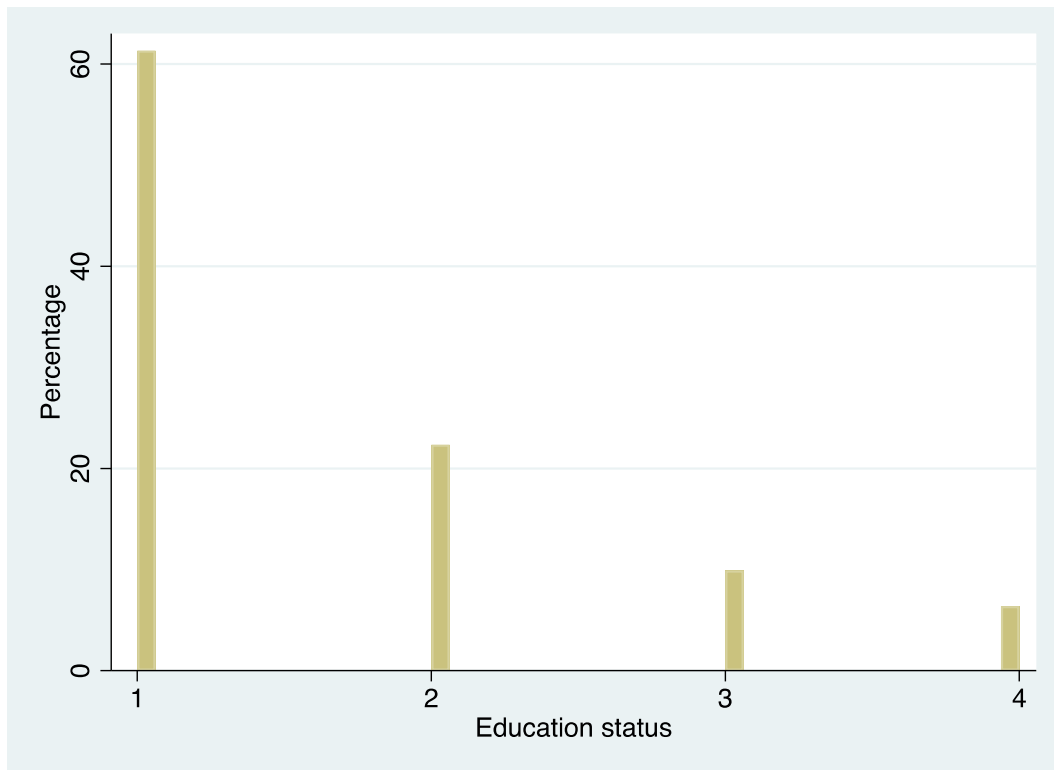


Figure 3 Percentage composition of individuals for the first hypothesis based on education

Note: The percentage is on the y axis, the education status on the x axis. Column 1 indicates an individual who has a high school diploma, column 2 indicates an individual who has a university bachelors' degree, column 3 indicates an individual who has a university honours/master's degree, and column 4 indicates an individual who answered "Do not know". The period is 2000 – 2010.

Table 3 Descriptive statistics of the data sample used for the second hypothesis for the period 2000 – 2010

Variable	Observations	Mean	Standard Deviation	Min	Max
UIF	10,031	0.01	0.10	0	1
Population group	10,031	1.75	1.22	1	5
Treatment	10,031	0.80	0.40	0	1
Female	10,031	0.66	0.47	0	1
Age	10,031	35.46	8.50	25	54
Education	10,031	1.68	1.09	1	4

Note: UIF, Treatment, and Female are dummy variables. Unemployed equals 1 if the individual is unemployed, 0 if they are employed. Treatment equals 1 if an individual is Black/African, Indian/Asian, or Coloured, and 0 if they are White. Female equals 1 if an individual is female, and 0 otherwise. Race and Education are categorical variables. Race is measured as follows: 1 equals a Black/African individual, 2 equals a Coloured individual, 3 equals an Indian/Asian individual, 4 equals a White individual, 5 equals Other. Education is measured as follows: 1 equals high school diploma, 2 equals university bachelors' diploma, 3 equals university honours/masters diploma, and 4 equals if an individual answered "Do not know". Age is a continuous variable measured in years. UIF equals 1 if an individual is unemployed and claims the UIF, while equals 0 if they are unemployed but do not claim the UIF.

Table 4 Average values (based on population group) of the data sample used for the second hypothesis for the period 2000 – 2010

Population group	Percentage of sample (%)	UIF (%)	Female (%)	Age (years)	Treated
Black/African	69.22	0.67	63.23	33.66	1
Coloured	7.07	0.56	60.37	38.93	1
Indian/Asian	3.53	3.67	69.49	37.51	1
White	20.00	1.55	79.56	40.06	0
Other	0.19	0.00	42.11	38.79	1

Note: The table gives the average values of certain indicators based on race category. The five race categories are indicated in the first column, and the indicators being measured are shown in the top row. Treated indicates whether this group is part of the treatment or control group, a 1 indicates treatment, a 0 indicates control group. The racial category "Other" is for any individuals who do not fall under one of the top four categories. UIF equals 1 if an individual is unemployed and claims the UIF, while equals 0 if they are unemployed but do not claim the UIF.

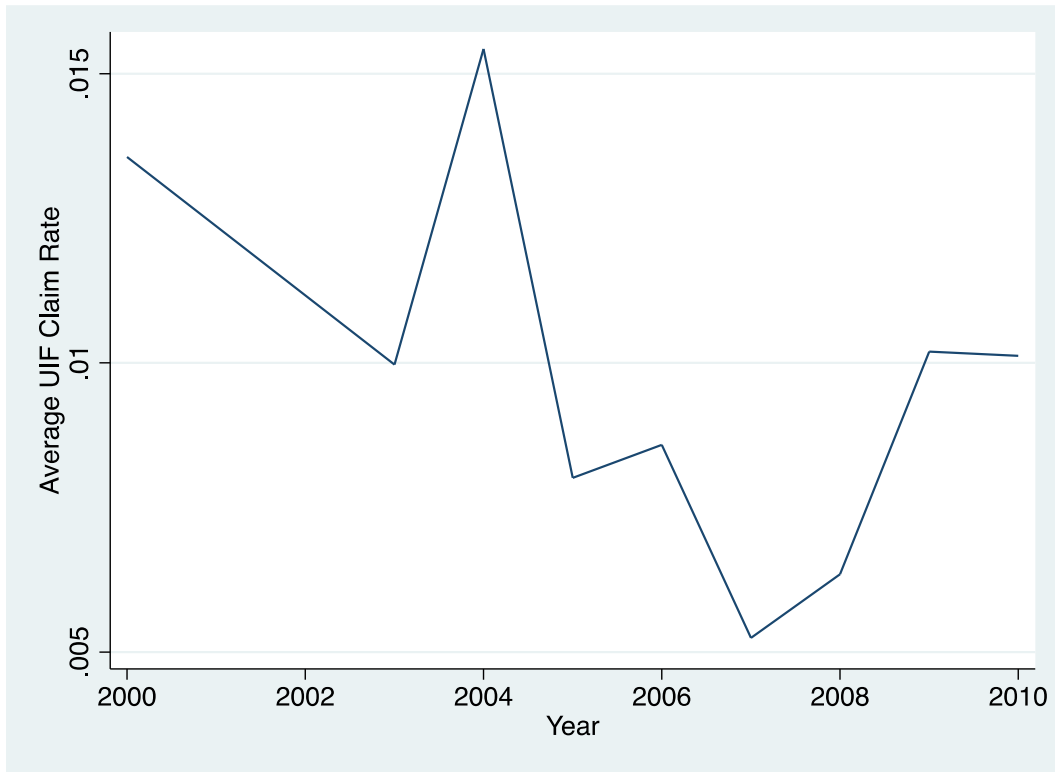


Figure 4 UIF Claim Rates for South African citizens for the period 2000 – 2010

Note: The year is on the x axis, and the UIF claim rate on the y axis. The UIF claim rate is measured between 0 and 1, thus the interval multiplied by 100 indicates the percentage of unemployed.

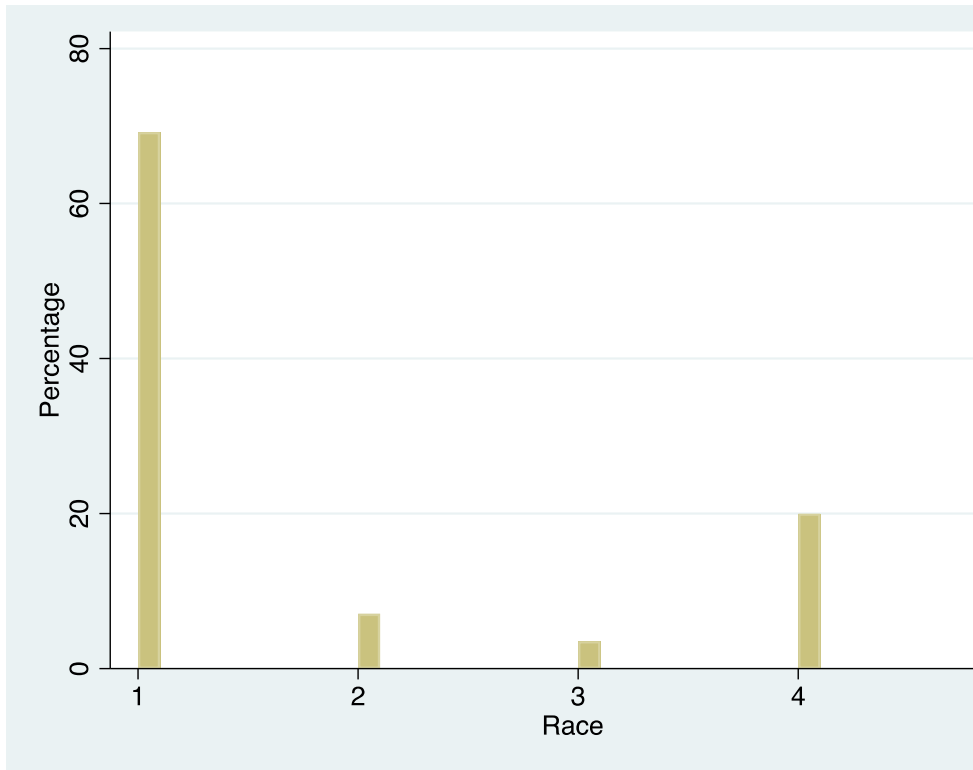


Figure 5 Percentage composition of individuals for the second hypothesis based on population group

Note: The percentage is on the y axis, the population group on the x axis. Column 1 indicates Black/African individuals, 2 indicates Coloured individuals, 3 indicates Indian/Asian individuals, and 4 indicates White individuals.

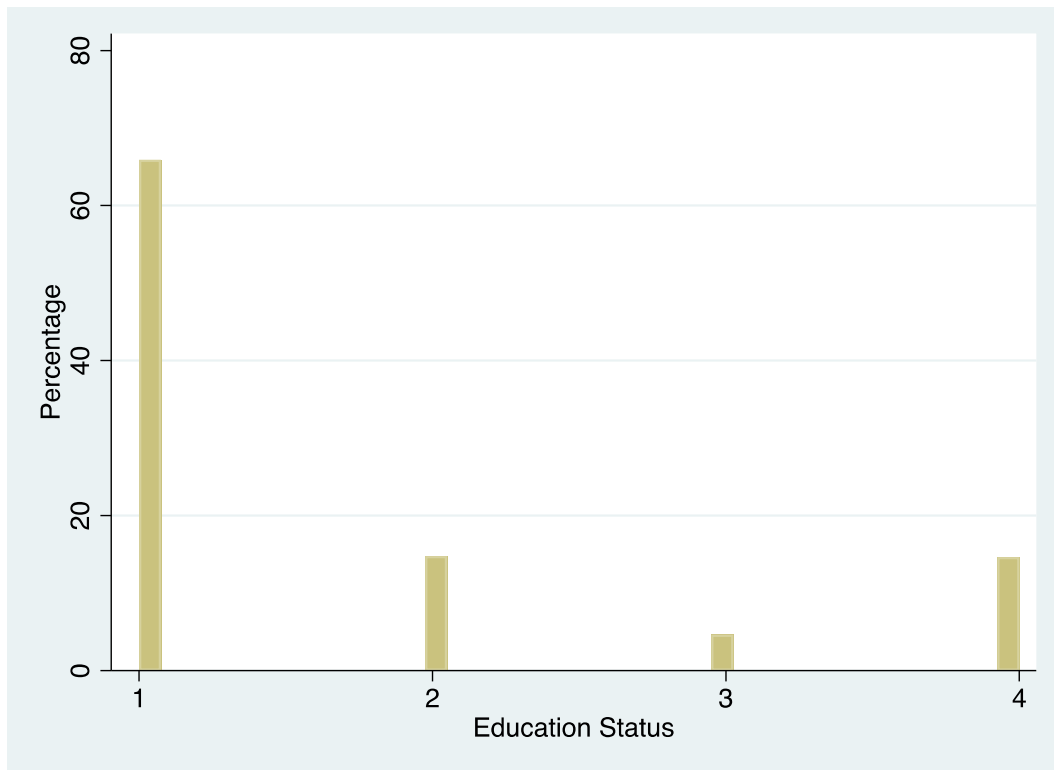


Figure 6 Percentage composition of individuals for the second hypothesis based on education

Note: The percentage is on the y axis, the education status on the x axis. Column 1 indicates an individual who has a high school diploma, column 2 indicates an individual who has a university bachelors' degree, column 3 indicates an individual who has a university honours/master's degree, and column 4 indicates an individual who answered "Do not know". The period is 2000 – 2010.

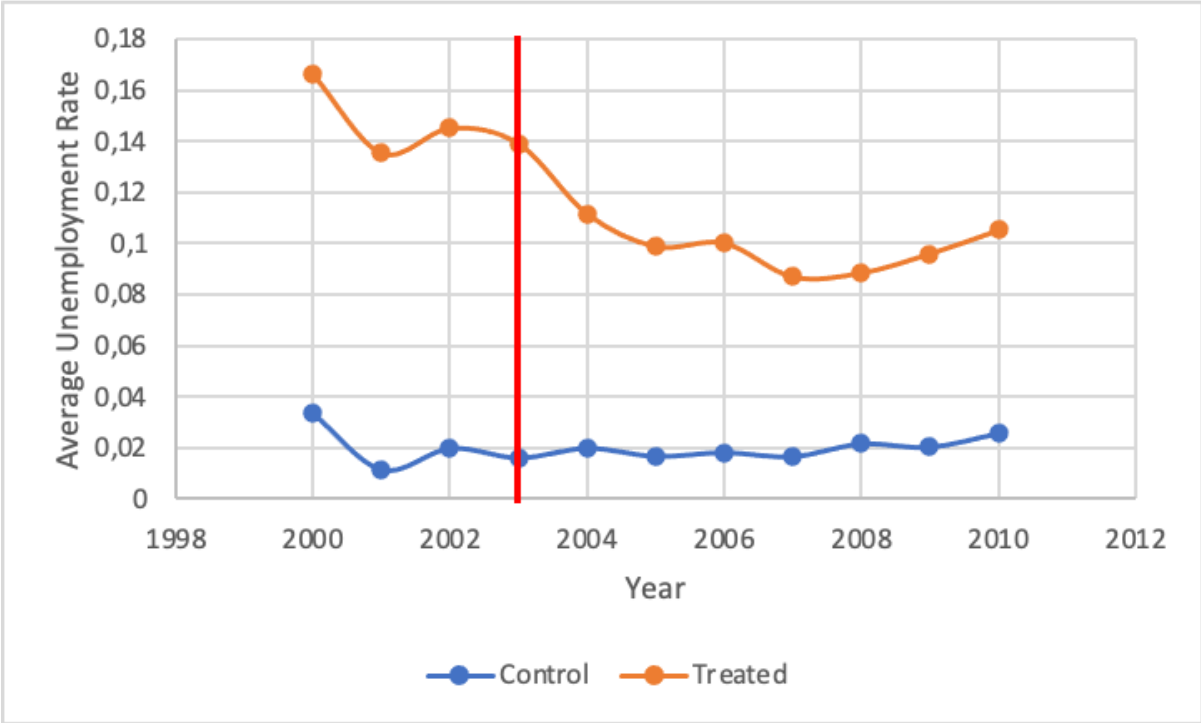


Figure 7 Share of unemployed individuals for the control and treatment group, pre and post 2003

Note: The year is on the x axis, and the average unemployment rate on the y axis. The period is from 2000 to 2010, thus before and after this period there is no data in the figure. The average unemployment dummy is between 0 and 1, multiplied by 100 gives the unemployment rate percentage.

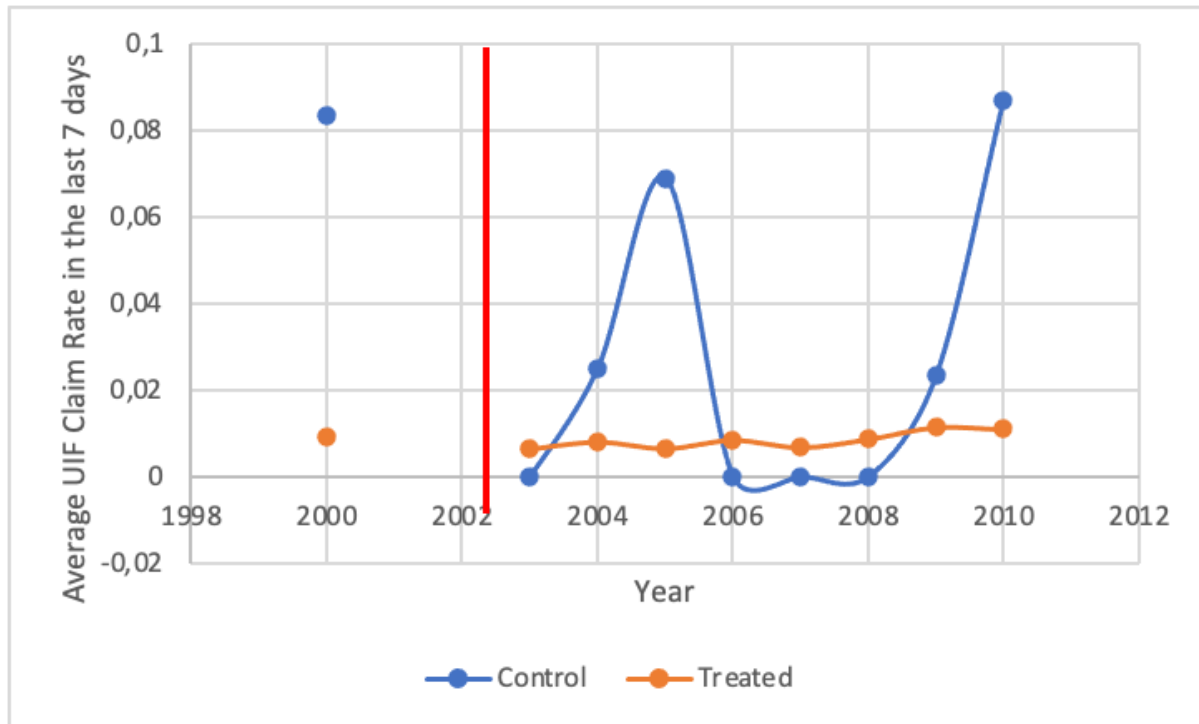


Figure 8 Share of unemployed individuals for the control and treatment group, pre and post 2003

Note: The year is on the x axis, and the average unemployment rate on the y axis. The period is from 2000 to 2010, thus before and after this period there is no data in the figure. The average unemployment dummy is between 0 and 1, multiplied by 100 gives the unemployment rate percentage.

Table 5 Differences-in-Differences equations to test both hypotheses regarding unemployment and UIF in South Africa between 2000 and 2010

Variable	Official unemployment Status	UIF Claim Rate
	(1)	(2)
Post*Treated	-0.039*** (0.007)	0.009 (0.019)
Post	-0.006 (0.004)	-0.011 (0.018)
Treated	0.094*** (0.007)	-0.013 (0.019)
Female	0.017*** (0.002)	-0.017*** (0.003)
Age	-0.007*** (0.000)	0.001*** (0.000)
Education	-0.023 (0.001)	-0.004*** (0.000)
Constant	0.315*** (0.007)	0.008 (0.019)
Observations	56,287	10,031

Note: Model (1) is investigating the first hypothesis, with the dependent variable being the unemployment rate. Model (2) is investigating the second hypothesis, with the dependent variable being the UIF claim rate. Model (2) only contains the unemployed portion of the overall sample, thus having a smaller number of observations. Standard errors are indicated in parentheses below the coefficients, and significance is indicated by the asterisk next to the coefficient. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table 6 Differences-in-differences regression equations to investigate heterogeneous effects between high school and university graduates

Variable	High school graduates		University graduates	
	Unemployment	UIF	Unemployment	UIF
	(1a)	(2a)	(1b)	(2b)
Post*Treated	-0.043*** (0.014)	0.167*** (0.046)	-0.051*** (0.009)	-0.005 (0.013)
Post	0.001 (0.011)	-0.172*** (0.045)	-0.005 (0.007)	0.014 (0.011)
Treated	0.108*** (0.013)	-0.186*** (0.046)	0.089*** (0.009)	0.010 (0.009)
Female	0.028*** (0.003)	-0.022*** (0.004)	0.000 (0.003)	0.003 (0.007)
Age	-0.008*** (0.000)	0.002*** (0.000)	-0.004*** (0.000)	0.001 (0.000)
Constant	0.326*** (0.026)	0.162*** (0.046)	0.74*** (0.010)	-0.036 (0.024)
Observations	40,074	19,681	3,382	728

Note: Models (1a) and (1b) are investigating the first hypothesis, with the dependent variable being the unemployment rate. Models (2a) and (2b) are investigating the second hypothesis, with the dependent variable being the UIF claim rate. Models (2a) and (2b) only contains the unemployed portion of the overall sample, thus resulting in a smaller number of observations. Standard errors are indicated in parentheses below the coefficients, and significance is indicated by the asterisk next to the coefficient. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table 7 Differences-in-Differences equations as robustness checks for the first hypothesis

Variable	Does not work	Expanded Unemployment
	(1c)	(1d)
Post*Treated	-0.060*** (0.011)	-0.008 (0.010)
Post	0.071*** (0.009)	-0.052*** (0.008)
Treated	0.063*** (0.010)	0.056*** (0.010)
Female	0.061*** (0.003)	0.061*** (0.003)
Age	-0.006*** (0.000)	-0.007*** (0.000)
Education	0.030*** (0.002)	0.016*** (0.002)
Constant	0.274*** (0.012)	0.341*** (0.011)
Observations	65,312	63,237

Note: Models (1) and (2) are investigating the first hypothesis, with the dependent variable being varying definitions of the unemployment rate. The official unemployment definition has three criteria: i) have not had work in the seven days leading up to the interview; ii) are ready to start working seven days after the interview; and iii) have been actively seeking employment within a month of the interview. Model (1) only takes into consideration criterion i), while model (2) considers criteria i) and ii), but not iii). Standard errors are indicated in parentheses below the coefficients, and significance is indicated by the asterisk next to the coefficient. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table 8 Parallel Trends Assumption Test via an Event Study for the first hypothesis

Variable	Unemployment
	(1e)
t – 1	0.013 (0.009)
Post	0.018** (0.008)
t + 1	-0.014** (0.006)
t + 2	-0.008** (0.004)
Treated	0.105*** (0.007)
Post*Treated	-0.039*** (0.007)
Female	0.016*** (0.002)
Age	-0.006*** (0.000)
Education	-0.002* (0.001)
Constant	0.287*** (0.010)
Observations	59,337

Note: Model (1) is investigating the PTA of the first hypothesis, with the dependent variable being the unemployment rate. The baseline year (t) is the year of implementation of the BBBEE, thus 2003. t – 1 indicates one year before 2003, and t + 1 refers to one year after 2003. Standard errors are indicated in parentheses below the coefficients, and significance is indicated by the asterisk next to the coefficient. * p < 0.1, ** p < 0.05, and *** p < 0.01.

Table A.1 Descriptive statistics for the first hypothesis based on population group (Black/African)

Variable	Observations	Mean	Standard Deviation	Min	Max
Unemployed	38,570	0.19	0.40	0	1
Treatment	38,570	1.00	0.00	1	1
Female	38,570	0.57	0.49	0	1
Age	38,570	37.08	7.87	25	54
Education	38,570	1.56	0.92	1	4

Note: Unemployed, Treatment, and Female are dummy variables. Education is a categorical variable. Education is measured as follows: 1 equals high school diploma, 2 equals university bachelors' diploma, 3 equals university honours/masters diploma, and 4 equals if an individual answered "Do not know". Age is a continuous variable measured in years. The period is 2000 – 2010.

Table A.2 Descriptive statistics for the first hypothesis based on population group (Coloured)

Variable	Observations	Mean	Standard Deviation	Min	Max
Unemployed	5,876	0.13	0.33	0	1
Treatment	5,876	1.00	0.00	1	1
Female	5,876	0.53	0.50	0	1
Age	5,876	38.71	8.08	25	54
Education	5,876	1.67	1.05	1	4

Note: Unemployed, Treatment, and Female are dummy variables. Education is a categorical variable. Education is measured as follows: 1 equals high school diploma, 2 equals university bachelors' diploma, 3 equals university honours/masters diploma, and 4 equals if an individual answered "Do not know". Age is a continuous variable measured in years. The period is 2000 – 2010.

Table A.3 Descriptive statistics for the first hypothesis based on population group (Indian/Asian)

Variable	Observations	Mean	Standard Deviation	Min	Max
Unemployed	2,752	0.14	0.35	0	1
Treatment	2,752	1.00	0.00	1	1
Female	2,752	0.47	0.50	0	1
Age	2,752	37.53	8.10	25	54
Education	2,752	1.68	0.81	1	4

Note: Unemployed, Treatment, and Female are dummy variables. Education is a categorical variable. Education is measured as follows: 1 equals high school diploma, 2 equals university bachelors' diploma, 3 equals university honours/masters diploma, and 4 equals if an individual answered "Do not know". Age is a continuous variable measured in years. The period is 2000 – 2010.

Table A.4 Descriptive statistics for the first hypothesis based on population group (White)

Variable	Observations	Mean	Standard Deviation	Min	Max
Unemployed	18,045	0.12	0.33	0	1
Treatment	18,045	0.00	0.00	0	0
Female	18,045	0.50	0.50	0	1
Age	18,045	40.06	8.08	25	54
Education	18,045	1.71	0.82	1	4

Note: Unemployed, Treatment, and Female are dummy variables. Education is a categorical variable. Education is measured as follows: 1 equals high school diploma, 2 equals university bachelors' diploma, 3 equals university honours/masters diploma, and 4 equals if an individual answered "Do not know". Age is a continuous variable measured in years. The period is 2000 – 2010.

Table B.1 Descriptive statistics for the second hypothesis based on population group (Black/African)

Variable	Observations	Mean	Standard Deviation	Min	Max
UIF	6,943	0.01	0.08	0	1
Treatment	6,943	1.00	0.00	1	1
Female	6,943	0.63	0.48	0	1
Age	6,943	33.66	7.69	25	54
Education	6,943	1.64	1.12	1	4

Note: UIF, Treatment, and Female are dummy variables. Education is a categorical variable. Education is measured as follows: 1 equals high school diploma, 2 equals university bachelors' diploma, 3 equals university honours/masters diploma, and 4 equals if an individual answered "Do not know". Age is a continuous variable measured in years. The period is 2000 – 2010.

Table B.2 Descriptive statistics for the second hypothesis based on population group (Coloured)

Variable	Observations	Mean	Standard Deviation	Min	Max
UIF	709	0.01	0.07	0	1
Treatment	709	1.00	0.00	1	1
Female	709	0.60	0.49	0	1
Age	709	38.93	9.28	25	54
Education	709	2.11	1.37	1	4

Note: UIF, Treatment, and Female are dummy variables. Education is a categorical variable. Education is measured as follows: 1 equals high school diploma, 2 equals university bachelors' diploma, 3 equals university honours/masters diploma, and 4 equals if an individual answered "Do not know". Age is a continuous variable measured in years. The period is 2000 – 2010.

Table B.3 Descriptive statistics for the second hypothesis based on population group (Indian/Asian)

Variable	Observations	Mean	Standard Deviation	Min	Max
UIF	354	0.04	0.19	0	1
Treatment	354	1.00	0.00	1	1
Female	354	0.70	0.46	0	1
Age	354	37.51	8.44	25	54
Education	354	1.70	0.93	1	4

Note: UIF, Treatment, and Female are dummy variables. Education is a categorical variable. Education is measured as follows: 1 equals high school diploma, 2 equals university bachelors' diploma, 3 equals university honours/masters diploma, and 4 equals if an individual answered "Do not know". Age is a continuous variable measured in years. The period is 2000 – 2010.

Table B.4 Descriptive statistics for the second hypothesis based on population group (White)

Variable	Observations	Mean	Standard Deviation	Min	Max
UIF	2, 006	0.02	0.12	0	1
Treatment	2,006	0.00	0.00	0	0
Female	2,006	0.80	0.40	0	1
Age	2,006	40.06	8.65	25	54
Education	2,006	1.65	0.86	1	4

Note: UIF, Treatment, and Female are dummy variables. Education is a categorical variable. Education is measured as follows: 1 equals high school diploma, 2 equals university bachelors' diploma, 3 equals university honours/masters diploma, and 4 equals if an individual answered "Do not know". Age is a continuous variable measured in years. The period is 2000 – 2010.

Table C.1 Proportion of different unemployment benefits used by the unemployed sample for the period 2000 – 2010

Type of benefit	Uses the benefit (%)	Does not use the benefit (%)
Odd jobs	0.02	99.98
Supported by person in household	77.92	22.08
Supported by persons not in household	15.66	84.34
Charity	0.82	99.18
UIF	0.87	99.13
Savings	8.94	91.06
Old age	5.03	94.97
Other sources (e.g. bursary, loan)	1.92	98.08
Observations	10,874	10,874

Note: All the individuals within the sample of 10,874 have indicated that they were unemployed at the time of answering the survey. As a follow up question, they were asked how they have been supporting themselves within the last 7 days, and these are indicated in the first column of the table. The individual answered that they either did or did not support themselves with the indicated benefits, and the percentage of individuals who do and do not use the specific benefit are indicated in the second and third columns.