Disability Grant and Individual Labour Supply: Evidence From South Africa*

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April 28, 2012

Abstract

Despite the explosive growth in the number of people receiving disability benefits in South Africa, very little is known about the labour supply effects of the benefits. This study aims at estimating the impact of the Disability Grant Programme (DGP) on labour force participation. Consideration is given to potential bias that may arise from unobserved confounding factors. We use data drawn from the 2007 wave of the General Household Survey (GHS) and implement a three-step methodology in a comparative perspective. Firstly, we implement an ordinary least squares regression followed by an instrumental variable regression to correct for possible endogeneity of DG take up. Finally, we check the sensitivity and robustness of the results by implementing a variety of propensity score matching techniques. The results overall suggest that the DGP has work disincentive effects, but the magnitude of the effects differs between parametric and non-parametric estimators.

Keywords*:* Disability Grant, Labour Force participation, Propensity score

Jel-Classification*:* H53, J21, J64, J22, J68

*This chapter is prepared as part of a PhD thesis on "Disability Grant and Labour Supply in South Africa" under the supervision of Ass Prof Ingrid Woolard, Ingrid.Woolard@uct.ac.za.

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1 Introduction

All over the world, governments and development agencies increasingly recognise cash transfers as an important component of poverty reduction. The popularity of such programmes stems from their inherent flexibility in targeting specific individual and households' varied needs. In line with that recognition, South Africa has one of the most substantive social protection systems in the developing world. The elderly people are provided for through a generous old age pension (OAP), children younger than 15 are catered for through the child support grant (CSG), while people with disabilities receive a means tested disability grant (DG).

Even as reliance on social protection programmes is increasing, concern has been raised on the potential distortionary effect the programmes induce in the labour market. In continental Europe and the United States, the declining labour force participation rates observed among the elderly has attracted a significant amount of research by authors attempting to investigate the interaction between social insurance programmes and labour force participation (Chen & van der Klaauw 2008, Campolieti 2004, Gruber 2000, Bound & Burkhauser 1999a). One body of literature identified generous and long lasting unemployment benefits as factors that potentially explain the low labour force participation rates (Blanchard & Wolfers 2000). Disability insurance (DI) programmes have been suggested as potential vehicles altering labour market behaviour (Staubli 2009, Autor & Duggan 2006, Haveman & Wolfe 1984b).

In South Africa, unlike the OAP and CSG whose reach and impact is the subject of a growing body of literature (Ranchhod 2009, Ardington, Case & Hosegood 2009, Aguero, Carter & Woolard 2007, Lund 2007, Case & Ardington 2006, Ranchhod 2006, Booysen & Van Der Berg 2005, Case 2004, Duflo 2000), very little is known about the labour supply effect of the DGP which targets working age persons with disabilities (Figure 1). This is in part because of paucity of disability related data, but most importantly the disincentive effect of disability cash transfers has for long been assumed to be economically insignificant because of low take up rates and high unemployment in most developing countries (Case & Deaton 1998). Indeed, in some countries take up rates of disability cash transfer programmes is very low (OŠKeefe 2007). However, the take up rate of the DGP in South Africa has explosively grown (Figure 2) in the last decade (Treasury 2007).

If determination of enrolment to the DGP was perfect, receipt of disability benefits would not affect the decision to participate in the labour market, as only those unable to work due to health conditions would be receiving the benefits. Nonetheless, because the determination process is imperfect and developing countries generally lack the administrative capacity required to run disability targeted programmes, moral hazard reporting is expected to take place (Parsons 1996). As a consequence, the disability assessment is inherently prone to classification errors (Mitra 2009) with some individuals receiving disability benefits even though they do not have disabilities (inclusion error), while other applicants may be rejected though they have disabilities (exclusion error) (Benitez-Silva, Buchinsky & Rust 2004, Nagi 1969).

Due to errors in disability tagging, it is not unusual that even in developing countries with high underemployment and unemployment, disability targeted programmes might induce efficiency losses through reductions in labour supply. In light of the generosity of potential benefits under the DGP and concurrent low levels of labour force participation observed among people with disabilities (Figure 3), the DG provides a potentially interesting explanation to the declining labour force participation rates among people with disabilities in South Africa.

The purpose of this paper is therefore, to evaluate if the DGP is distorting labour supply decisions among South Africans with disabilities. We estimate the effect of receiving disability benefits on labour force participation of recipients using a three-step methodology. Firstly, we implement an ordinary least-square regression (OLS) to control for observables. Secondly, we use an instrumental variable regression (IV) to address potential endogeneity of DG take up. Finally, as our instrument might be weak, we try to control for the endogeneity of participation in the DGP with a propensity score matching method (PSM) to check the robustness of OLS and IV results.

The paper is organized as follows. Section 2 provides a brief background of the DGP in South Africa. In section 3 we review previous evidence on the effect of disability benefits and labour force participation, while section 4 describes the data. Section 5 presents the modelling strategies. Section 6 presents the results of implementing OLS and IV regression techniques. Section 7 tests the robustness of the outcomes using a propensity score matching methodology. Section 9 concludes with a discussion of the implications of our findings.

2 The Disability Grant Programme

The design of the social assistance system in South Africa is anchored on full employment, wherein it is implicitly accepted that able-bodied adults can provide for themselves through work. As a result, unemployed people rely on pensioners, transfers from employed family members and (increasingly) on disability grants to survive (Nattrass 2006). The DG is means tested and subject to a medical eligibility criteria. It is provided for through an Act of Parliament and is funded by the National Treasury. Applicants for this grant must be 18 years and above, and below the age of 60. After a DG beneficiary attains the age of 60; the DG is automatically converted to an equally non-contributory old age pension that is also means tested. Potential applicants should demonstrate that they are medically unfit to work as a result of a disability. The grant can be awarded on a temporary basis, usually six months, in cases where the applicant is expected to resume a productive life, or on a permanent basis if no change in the individual's functional abilities is expected.

Applicants must be citizens or permanent residents of South Africa and be living in South Africa at the time of applying for the grant. Where the applicant is below the age of 18, the parents or guardian should apply for the care dependency grant instead. Should the disability be as a result of an accident at work or a motor vehicle accident, one is also eligible to have a compensation claim. Incarcerated people, and those who live in state institutions (such as old age homes), psychiatric hospitals and state treatment centres are not eligible for the grant. The grant is also not accessible to individuals who are getting state care for drug rehabilitation and those who refuse to undergo treatment.

2.1 Assessment

The provisions of the Social Assistance Act of 1992 require that, a person seeking benefits under the DGP applies at an office of the South African Social Security Agency (SASSA). After the applicant has gathered the required documentation to support his/her application, the applicant is then referred to a state appointed medical doctor to determine the extent of his/her disability. The examiner at this stage, with the aid of vocational and medical consultants, determines the eligibility of the applicant to receive disability benefits.

Historically, the assessment has been conducted by medical practitioners appointed by the state. The practitioner, on completion of the examination process, compiles an assessment report upon which, the Department of Social Development will base their final decision. The report is valid for thirty days and if the application is approved, payment will be effected after three months. If the application is rejected an individual is allowed to lodge an appeal within thirty days of receipt of the rejection advice.

Medical practitioners receive little or no training in medical examination of applicants. Due to the shortage of health practitioners in South Africa, particularly in rural areas, coupled with the rising health care burden, it has become an increasing challenge to provide these medical assessments. Furthermore, where resources are scarce, medical practitioners may resent and try to avoid work which they see as administrative –such as assessments for grants –rather than the clinical work for which they were trained.

Partly because of these issues, and mindful of the challenges in releasing equitable and efficient access to disability and care-dependency grants, the Department of Social Development promulgated regulations in 2001, enabling assessment panels to make the assessments for grants. Medical practitioners may be included in the review panel, though it is not mandated for them to be part of the composition. Members of the review panel are required to evaluate applicants' submitted information and determine disability for both disability and care-dependency grants. Review panels may have flexible membership, but should have representation from the social security board and a rehabilitation therapist (nurse, social worker, occupational, psychotherapist, audio visual therapist etc.). The panel should also include a representative from the disability sector or a reputable member of the community such as a priest, chief, magistrate, or any person who is familiar with the community and its circumstances.

2.2 Calculation of Benefits

Individuals whose financial status is below a certain threshold are eligible for the grant. The means test depends on the applicant's level of income (if one is not married), or on the joint income of both the applicant and spouse (if married). As of February 2009, a single person's income must be less than R23 500 per year, and the value of his/her assets must be less than R451 200 for the person to be eligible. In this case, assets are defined as any items of value that one owns, such as a car, a television and an oven. If the applicant owns a house and lives therein (not lease out), then this house is not included in the individual's asset value. For married individuals, joint income must not be more than R43,700 and the value of their joint assets must amount to less than R902,400 and the house is treated in the same way as above

2.3 Trend in Disability Grant Statistics

The DG benefits for which individuals with disabilities are potentially eligible are generous. The maximum payout has increased from R500 in 2000, to R1110 by 2010 (Figure 4), representing an average annual growth rate of 9 per cent. The current payout is approximately more than 100 percent of the black median per capita income (Edmonds 2006).

Perhaps as a result of the generous benefits, classification errors in determining disability (Figure 5), and leniency in the determination process, there was a tremendous growth in the number of beneficiaries between 2001 and 2004. The number of DG recipients more than doubled from 0.6 million in 2001 to 1.3 million by 2004 (Figure 6), representing an average annual growth rate of 7.6 percent. Total payments grew three fold to reach R12 billion per month (Figure 7). At the same time, the levels of labour force participation among recipients remained depressed compared to non-recipients. As a result, concern grew on whether the DGP is distorting labor supply decisions among people with disabilities who are able to work, and thus create work disincentives and a culture of dependency (Standing 2008, Nattrass 2006).

3 Related Literature

3.1 Theory

The link between the DG and labour force participation is rather complex. Any analysis of the two should investigate whether or not receipt of the DG by individuals acts as a disincentive to seeking or keeping employment. The means test that determines eligibility to the DGP seems to penalise and de-motivate people with private savings, or those who want to take up employment. People with disabilities are more likely to rely on the DG because of their exclusion from employment opportunities (Boardman, Grove, Perkins & Shepherd 2003, Manning & White 1995). Even those that get jobs are likely to be employed on a temporary basis and generally lowly paid (DeLeire 2000, Burkhauser & Daly 1996). As a result, they often weigh the risk of losing their jobs against an otherwise guaranteed source of income through the DG (Tschopp, Perkins, Hart-Katuin, Born & Holt 2007, McLaren, Philpott, Mdunyelwa & Peter 2003). They argue that in the event that they are laid off from their jobs, they risk facing long delays before they start receiving government benefits again (Mitra 2005).

3.1.1 Potential causal mechanisms

Reservation wage In the standard labor leisure choice model, the reservation wage is a fundamental aspect of the decision to work or not to work. The reservation wage is the amount an individual would need to earn at work in order to accept a job. For a DG beneficiary to return to work the market wage would need to exceed the reservation wage. If leisure is assumed to be a normal good in the labour leisure choice model, the reservation wage increases as non-labour income increases (Borjas 2000). As the disability benefits increase, non-labour income also increase, and ultimately workers want to consume more leisure and therefore a larger wage is required to induce the person to work (Bloemen & Stancanelli 2001, Gorter & Gorter 1993, Jones 1988, Feldstein & Poterba 1984).

Health effect The decision not to work by DG beneficiaries may not be completely explained by the reservation wage effect. Even in the presence of classification errors, the likelihood of receiving disability benefits is high among individuals with severe disabilities diminished health stocks. At the same time, individuals with severe disabilities have a higher probability of not engaging in market activities. Therefore, the decision not to work in such circumstances may be a result of poor health than preference for leisure (Kreider & Pepper 2007, OŠDonnell 1998, Barnes 1992).

3.2 International Evidence

While the OAP and CSG have been carefully studied, very little evidence is available on the DGP (Mitra 2005, Mitra 2009). Therefore this section mostly presents international evidence on the effect of disability benefits and labour supply.

Since the 1960s, the labour force participation rates of the elderly males in OECD countries has declined form 80 to 65 percent despite improvements in aggregate health (Staubli 2009). This created an enormous interest from researchers seeking to explain what seemed like an appalling phenomenon. For this reason today we have a substantial amount of literature focusing on the behavioural effects of disability insurance programmes as a possible explanation of the declining labour force participation rates (Gruber 2000, Bound 1989, Haveman & Wolfe 1984a, Parsons 1980). Despite literature on social security and labour supply having been amply surveyed in the developed world, notably in the US and Canada[1], there still remains substantial uncertainty on the impact of the program.

Studies on behavioral effects of disability programs may be categorised into two groups. On one hand we have studies that rely on time series variations in the law to identify the effect of changes in benefits or other parameters of the social security programmes. The other arm constitutes studies that rely on cross sectional variations (e.g. across families) in benefits to identify the effect of social security benefits. In between the two arms we have studies that utilize panel data potentially drawing on both time series and cross-sectional variation in benefits

Behavioural cross sectional analyses suffered from the fact that factors that determine benefits (e.g. previous earnings) are likely to be correlated with labour force attachment and thus confound the estimated effects of the disability insurance programme. On the

[1] Bound & Burkhauser (1999b)provide a comprehensive review up to the year 1999

other hand, studies which utilize time series analysis encounter a situation where labour force participation trends downward when social security benefits trend up. The causal analysis is thus affected by whether the negative relationship between benefits and labour supply is causal or is just a reflection of other variables that have also trended over time such as income or pension wealth (Krueger & Pischke 1991) .

Cross-sectional studies generally proceed by modeling labour force participation as a function of potential disability benefits receipt. The pioneering study in this block was by (Parsons 1980), who estimated an elasticity of labour force non-participation with respect to disability benefits. With a coefficient range of 0.4 to 0.93, his upper bound estimate implied that increases in disability benefits over the 1960s and 1970s could explain the entire trend of non-participation.

However, Bound (1989) argued that this type of strategy is likely to yield misleading inferences for the effect of DI generosity on labour force participation. Since DI benefits are a redistributive function of past earnings which is common to all workers, variation in potential benefits comes primarily from differences in earnings history across workers. This leads to a fundamental identification problem in modeling the effect of potential DI benefits on work decisions; a finding that workers with higher potential DI replacement rates are more likely to leave their jobs may simply reflect the fact that low earning workers have less desire to continue working. What is clearly needed is to identify the behavioral impact of DI benefits is variation in program generosity which is independent of underlying tastes for work.

Haveman & Wolfe (1984b) attempted to address this identification problem by replacing the actual replacement rate with a predicted value obtained from a first stage regression of the replacement rate on a set of exogenous variables. In contrast to the earlier studies, they found much lower elasticity estimates of between 0 and 0.03. To identify the replacement rate effect (or the separate wage and disability benefit effects) some exogenous variables that determine wages or (and) disability benefits must be excluded from the labour force participation equation. However, without a convincing justification for their exclusion restrictions their estimates potentially be incredible.

While these earlier cross-sectional studies based on US data either ignored the potential endogeneity of the replacement rate or relied on arbitrary exclusion restrictions for identification, three recent studies explore alternative identification approaches for dealing with the endogeneity of disability benefit receipt. Gruber (2000) employed a difference in difference methodology to exploit an exogenous policy change conducted in Canada in 1987, where the benefit levels of the rest of the country were adjusted upwards to meet those of the Quebec Province. Using data covering the 1985–1989 period, he estimated the elasticity of labor force non-participation with respect to DI benefit levels to be between 0.28 and 0.36. The identification approach and the credibility of his estimate depend on the validity of the assumption that any changes in the relative labor market conditions in Quebec as compared to the rest of the country during this period, were uncorrelated with the differential change in DI benefits.

Autor & Duggan (2003) also use differential time variation in average benefits across geographical regions to identify the impact of DI on the LFP of low skilled workers. Using state level data from the CPS and the Social Security Administration (SSA), they exploited the variation in the replacement rate due to differences across states and over time in the wage distribution, to identify the effect for low-income workers. They maintained that the widening dispersion of earnings in the US, combined with the progressivity of the disability benefits formula and the fact that DI benefits are set nationally and do not adjust for variation in regional wage levels, provide an exogenous measure of program generosity independent of workers' underlying taste for work. They concluded that the DI system provided many low-skilled workers with a viable alternative to unemployment. They estimated that the overall unemployment rate in 1998 would have been one half a percentage point higher in the absence of the DI program. Unfortunately, their reported estimates do not allow calculation of an elasticity that can be compared to those in other studies. The identification strategy relies on the absence of other differences across states in both the changes in labor market conditions over time as well as the impact of such changes on labor supply, which seems problematic since variation in the wage distribution over time across states can itself be expected to directly affect labor supply.

While most literature has focused on the effect of potential benefits on labour supply, there are a number of other tools available to the DI policy maker who is trying to mitigate moral hazard. Marvel (1982), Halpern & Hausman (1986), Parsons (1991) and Gruber & Kubik (1997) examined the effect of the DI denial rate on applications to DI on labor force participation. Halpern and Hausman, and Parsons found a strong association between denial rates and labour force participation. Gruber and Kubik also found a strong association between denial rates and the labor force participation of older workers; they estimated that each 10 percentage rise in denial rates led to a statistically significant 2.8 percent fall in labour force participation among $45 - 64$ year old males.

De Jong, Lindeboom & van der Klaauw (2006) investigated the effects of intensified screening of disability insurance benefit applications. A large-scale experiment was setup where in 2 of the 26 Dutch regions case, workers of the disability insurance administration were instructed to screen applications more intense. The empirical results showed that intense screening reduces long-term sickness absenteeism and disability insurance applications. This provides evidence both for direct effects of the more intensive screening on work resumption during sickness absenteeism and for self-screening by potential disability insurance applicants.

Staubli (2009) explored the labor supply effects of a large-scale policy change in the Austrian disability insurance programme, which tightened eligibility criteria for older men. Using administrative data on Austrian private-sector employees, the results of a difference-in-difference empirical strategy suggested a substantial and statistically significant decline in disability enrolment of between 11.58 and 14.3 percentage points and a modest increase in employment of 3.2 to 4.0 percentage points.

4 Data and Descriptive Statistics

We estimate the effect of receiving disability benefits on individual labour supply, using data drawn from the General Household Survey (GHS). The GHS is a nationally representative, large-scale cross-sectional survey of approximately 28000 South African households spanned across all nine provinces of the country. The first round of the survey was conducted in 2002, with subsequent waves conducted every year. We use the 2007 wave to study the labour supply effects of DG receipt. The survey includes detailed information on socioeconomic and demographic indicators at household and community level, as well as information on social grants receipt and disability status at individual level.

4.1 Variables

As this paper aims at assessing the labour supply impact of receiving DG benefits, the dependent variable is own labour force participation. Labour force participation is 1 if an individual participates in the labour market an 0 otherwise. Given the dichotomous nature of the variable, we assume that the individual faces the choice between participating in the labour market or not. We eliminate the self-employed from the sample because there are likely to be interpretational inaccuracies among the respondents.

The variable of interest in this study is receipt of DG benefits. In order to construct this variable, we first created a dummy variable for disability. An individual is coded as having a disability if the response to the question, 'Do you have a limitation in daily activities, at home, at work or at school, because of a long term physical, sensory, hearing, intellectual, or psychological condition, lasting six months or more?' is yes. This self-reported measure though widely used is likely to suffer from endogeneity (arising from measurement error) especially when used to model the effect of own disability on labour supply (Bound 1991). Out of the individuals who report having disabilities, we created a dummy variable coded 1 if the individual receives the DG and 0 otherwise. This becomes our treatment variable in subsequent analyses.

The potential labour market participants are assumed to make decisions based on their individual characteristics. We thus include several variables presumed to have an influence on labour force participation. Information on race, age, educational attainment, marital status and type of disability is included at individual level. Household characteristics are controlled for in the labour force participation equation by variables such as the presence of infants, children aged 1 to 7 years and children aged 8 to 15 years in the household. Similarly the presence of a pensioner in the household is also controlled for as part of household effects. Community variations in employment opportunities are proxied by provincial dummies, district narrow unemployment rates, district narrow labour force participation rates, and distance to the welfare office among others.

Table 1 provides the characteristics of the ultimate sample constructed according to the treatment status. A total of 3293 individuals reported to have disabilities, out of which 1675 individuals (42.7 percent) receive disability benefits. The racial structure of people with disabilities is moderately similar between the treated and control cases. Both are dominated by Africans with a share of over 77 percent. The major difference with the race set up occurs among Coloureds. It appears individuals within this population group are more represented in treated cases than in the control group.

Table 1: Descriptive statistics of selected variables used in estimations

	Treated N=1675		Control N=2248		Difference	
Variable	Mean	(SD)	Mean	(SD)	(T-C)	p-value
LFP Status						
Employed	0.04	(0.20)	0.13	(0.33)	-0.08	0.000
Narrow unemployed	0.01	(0.12)	0.04	(0.20)	-0.03	0.000
Broad unemployed	0.02	(0.13)	0.06	(0.24)	-0.03	0.000
Narrow labour force	0.06	(0.23)	0.17	(0.37)	-0.11	0.000
Broad labour force	0.06	(0.24)	0.19	(0.39)	-0.13	0.000
Race						
African	0.77	(0.42)	0.79	(0.40)	-0.02	0.039
Coloured	0.18	(0.39)	0.13	(0.34)	0.05	0.000
Asian	0.02	(0.12)	0.02	(0.13)	0.00	0.659
White	0.03	(0.18)	0.05	(0.23)	-0.02	0.001
Age groups						
Age	42.08	(27.50)	49.87	(55.01)	-7.79	0.000
15-24 years	0.10	(0.29)	0.17	(0.37)	-0.07	0.000
25-34 years	0.18	(0.38)	0.19	(0.40)	0.01	0.247
35-44 years	0.25	(0.44)	0.23	(0.42)	0.02	0.212
45-54 years	0.31	(0.46)	0.25	(0.43)	0.06	0.001
55-65 years	0.17	(0.37)	0.16	(0.36)	0.01	0.600
Marital status						
Single	0.57	(0.49)	0.46	(0.50)	0.11	0.000
Married	0.23	(0.42)	0.26	(0.44)	-0.03	0.053
Cohabit	0.07	(0.26)	0.06	(0.23)	0.01	0.038
Widowed	0.08	(0.28)	0.19	(0.39)	-0.11	0.000
Divorced	0.04	(0.20)	0.04	(0.19)	0.00	0.560
Educational Attainment						
Years of education	4.78	(4.17)	4.72	(4.31)	0.06	0.630
No Education	0.30	(0.46)	0.31	(0.46)	-0.01	0.657
Primary	0.47	(0.50)	0.47	(0.50)	0.00	0.862
Secondary	0.16	(0.37)	0.13	(0.34)	0.03	0.004
Matric	0.05	(0.23)	0.06	(0.23)	-0.01	0.942
Diploma	0.01	(0.07)	0.02	(0.15)	-0.01	0.000
Degree	0.00	(0.05)	0.01	(0.09)	-0.01	0.021
Literacy						
Can read	0.60	(0.49)	0.56	(0.50)	0.04	0.021
Can write	0.59	(0.49)	0.56	(0.50)	0.03	0.043
Province						
Gauteng	0.04	(0.21)	0.08	(0.27)	-0.04	0.000
Eastern Cape	0.18	(0.38)	0.13	(0.34)	0.05	0.000
Nothern Cape	0.07	(0.26)	0.09	(0.28)	-0.02	0.172
Free State	0.09	(0.28)	0.09	(0.29)	0.00	0.466

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Table 1 – *Continued from previous page*

	Treated		Control		Difference	
	N=1675		N=2248			
Variable	Mean	(SD)	Mean	(SD)	(T-C)	p-value
KwaZulu Natal	0.26	(0.44)	0.25	(0.43)	0.01	0.655
North West	0.09	(0.29)	0.12	(0.33)	-0.03	0.006
Western Cape	0.12	(0.32)	0.08	(0.27)	0.04	0.000
Mpumalanga	0.07	(0.26)	0.10	(0.30)	-0.03	0.005
Limpopo	0.08	(0.27)	0.07	(0.25)	0.01	0.103
Child Status						
No children	0.33	(0.47)	0.34	(0.47)	-0.01	0.732
Infants present	0.08	(0.28)	0.08	(0.27)	0.00	0.806
Children 1-8 yrs present	0.38	(0.49)	0.39	(0.49)	-0.01	0.628
Children 8-15 yrs present	0.20	(0.40)	0.19	(0.39)	0.01	0.406
Old Aged Adults						
Over 60 year old present	0.34	(0.47)	0.51	(0.50)	-0.17	0.000
Local labour market conditions						
District unemployment rate	0.25	(0.09)	0.25	(0.08)	0.00	0.216
District narrow LFP	0.52	(0.11)	0.52	(0.11)	0.00	0.382
Disability						
Physical	0.49	(0.50)	0.39	(0.49)	0.10	0.000
Sight	0.07	(0.26)	0.22	(0.42)	-0.15	0.000
Hearing	0.05	(0.22)	0.17	(0.38)	-0.12	0.000
Speech	0.04	(0.20)	0.03	(0.16)	0.01	0.005
Mental	0.21	(0.41)	0.12	(0.32)	0.09	0.000
Emotional	0.13	(0.34)	0.07	(0.26)	0.06	0.000
Distance to public transport						
0-14 minutes	0.71	(0.45)	0.67	(0.47)	0.04	0.003
15-29 minutes	0.18	(0.39)	0.20	(0.40)	-0.01	0.875
30-44 minutes	0.04	(0.19)	0.06	(0.23)	-0.02	0.252
45-59 minutes	0.02	(0.13)	0.01	(0.12)	0.00	0.110
Over 60 minutes	0.02	(0.14)	0.02	(0.14)	0.00	0.056

On average individuals in the treatment group are 42 years old with 4.8 years of schooling, whilst individuals in the control group are 50 years old with 4.7 years of schooling. The key difference within the age structure occurs among individuals aged between 18 and 24 years: treated individuals are less likely to be in this age group compared with individuals in the control group. Pensioners are more represented in control households than in treated households, whilst individuals with physical disability are more prevalent in the treated group compared with the control group. With regards to educational attainment, provincial dummies, children status, local labour market conditions, and distance to the welfare office, there are no substantial differences between the treated group and the control group. The table thus highlights the role of randomization: it appears the distribution of covariates between treated and control groups is overall not significantly different.

5 Modelling Strategy

5.1 Theoretical Model

5.1.1 Static Model of labour supply

The labour supply effect of DG receipts can be modelled through a static model of labour supply. Following (Cahuc & Zylberberg 2004, Kaufman & Hotchkiss 2000, Ehrenberg & Smith 2000, Killingsworth 1983), we consider an individual in the working ages of 18 to 60 years who reports having a disability. The individual is faced with a choice to allocate time between market and non-market activities. Each choice stems from the inherent intention of the individual to maximise an independent utility function composed of consumption and leisure. The utility is maximised subject to a budget constraint (Blundell & Macurdy 1999, Leuthold 1968). Therefore, let h and C denote the individual's hours of work and private consumption respectively. The price of the consumption is considered to be a numaraire. The individual's utility is thus

$$U = f(1 - h, C) \tag{1}$$

where U is strongly quasi-concave, strictly monotone (increasing) and twice continuously differentiable. Also, let w and y be the individual's wage income and non-labour income respectively. In seeking to maximise utility, the individual is constrained by an income level required to purchase consumption and by implication leisure time, thus we have

$$C = wh + y \tag{2}$$

The individual choice problem is thus

$$\max_{h,C} U(1-h, C) \tag{3}$$

subject to

$$wh + y = C \tag{4}$$

5.1.2 Including the disability grant

The above framework models an individual's labour force participation and hours of work, h, as a function of individual preferences, unearned income y and potential wage w. The labor force participation depends on whether the potential wage exceeds the individual's reservation wage(Kaufman & Hotchkiss 2000). The potential wage is a function of human capital, and thus traits such as age, race, education and local labour market conditions. On the other hand, the reservation wage reflects the valuation of an individual's non-market time, and depends on factors such as individual's disability (health) status D, taste for leisure and unearned income y. Unearned income is composed of the individual's income net of an earnings w. Thus, an individual's labor force participation h is ultimately a function of unearned income y, disability status H, and other socio-economic characteristics that affect the reservation wage and potential wage w:

$$h = f(y, D, w) \tag{5}$$

The individual disability status (D) has two implications; the health effect (H) discussed earlier and potential transfer payment component (DG). Therefore unearned income y, includes DG and other socio-economic factors x:

$$y = g(DG, x) \tag{6}$$

Thus

$$h = f(g(DG, x), H, w) \tag{7}$$

Substituting (7) in (3) gives

$$\max U[(1 - f(g(DG, x), H, w)), C] \tag{8}$$

subject to

$$w[f(g(DG, x), H, w] + g(DG, x) = C \tag{9}$$

It is clear that the solution to the above model suggest that the DG affects labour participation through the health effect and pure-income effect. Its however, impossible to adequately separate the two effects into standalone components in an empirical framework. As an attempt, the various types of disability are included in the empirical analyses to control for the health effect. We are assuming each type of disability represents a different individual health state. For example, an individual with a physical disability is accordingly expected to have a different probability of performing market activities compared with an individual with a hearing disability.

5.2 Empirical Models

5.3 The ordinary least squares common effect model

Until recently, the standard (and almost only) way to estimate the effect of treatment on labour market outcomes with cross sectional data was to control for observable differences between treated and non-treated individuals using ordinary least squares (OLS) linear regression (Vandenberghe & Robin 2004). Consistent with this approach, let Y_i be the probability of labour force participation (outcome measure), and D_i be the treatment indicator, where $D_i = 1$ if an individual with a disability receives the DG and $D_i = 0$ if an individual with a disability does not receive the DG. The observed labour force participation outcome is therefore estimated using the following standard probit regression:

$$Y_i = \alpha + \beta X_i + \delta D_i + \varepsilon_i \tag{10}$$

where Y_i is the observed probability of labour force participation (= 1 if an individual participates in the labour market and 0 if not), X_i is a vector of control variables at the individual, household and community levels and ε_i is the error term proxying unobservables that affect labour force participation.

The variable X_i is a vector of demographic and socio-economic covariates that affect the likelihood of participating in the labour market. It therefore includes variables such as age, race, educational attainment, household composition, marital status, gender, and local labour market conditions. In this base model or the "benchmark" case, the treatment dummy gives the coefficient δ for the average effect of DG on the probability of labour force participation of the recipients (ATT). If the explanatory variables, X_i perfectly control for the determinants of participating in the labour market (individual characteristics and other factors), the estimated $\widehat{\delta}$ with OLS will yield unbiased estimates of ATT. This approach assumes that there is no correlation between the DG take up and unobservable factors that affect labour force participation.

5.4 Instrumental Variable (IV) two-stage least squares regression.

The assumption of no correlation between DG take up and unobservable factors is unfortunately too strong especially in relation to issues of disability. Of concern is the possibility of endogenous participation in the DGP. Since admission to the DGP is not on voluntary basis, DG recipients might have specific characteristics that might bias the ATT estimated with OLS. Specifically, enrolment is likely to be higher among individuals with severe disabilities, a possibility that simultaneously reduces their likelihood of participating in the labour market. Therefore the coefficient associated with the DG dummy may be confounded with the effect of the unobserved (selection) variables. Controlling for the type of disability in (10) may potentially reduce the bias, but not completely remove the confounding effect. It is therefore important to control for the adverse selection problem, and ultimately reduce the distortion on the labour supply impact of the DGP.

In order to control for the selection bias in DG take up, we implement an instrumental variable (IV) estimation strategy. This strategy theoretically consists of estimating a two-stage regression model. In the first stage, the treatment outcome (probability of receiving disability benefits) is estimated against all the exogenous variables, X_i and the instrument Z. The instrument introduces an element of randomness into assignment to treatment. We thus have

$$D_i = \alpha + \lambda X_i + \tau Z + \eta_i \tag{11}$$

The predicted $\widehat{D_i}$ from (11) is added to the regression of

$$Y_i = \alpha + \beta X_i + \delta \widehat{D_i} + \varepsilon_i \tag{12}$$

in the second stage. If a suitable instrument exists, (11) and (12) will give an unbiased estimate of ATT. Failure to find a good instrument has often been the major drawback affecting reliability of IV estimates. Z qualifies to be a valid instrument if it affects the probability of receiving the DG, without itself being affected by any confounding factors that influence probability of participating in the labour market - outcome variable (Wooldridge 2002). Therefore

$$E(D_i|Z) \neq 0 \tag{13}$$

but

$$E(Z|\varepsilon_i) = 0 \tag{14}$$

We have opted for a categorical variable, $DIST$, distance from the respondent's place of residence to the nearest public transport as our instrument for receipt of the DG. Table 5.4 presents the marginal effects of a probit regression of DG take up on distance from the welfare office. The results confirms that the instrument fulfils the first condition to be an instrumental variable candidate. The marginal effect of being located far from public transport significantly reduces the likelihood of receiving disability benefits.

Table 2: Sensitivity of disability grant take up to distance to the nearest welfare office

Variable	All individuals with disabilities (1)	Males with disabilities (2)	Females with disabilities (3)
Dist 15-29	-0.030	-0.049	-0.016
	(0.036)	(0.053)	(0.047)
Dist 30-44	0.025*	-0.025	-0.100*
	(0.038)	(0.055)	(0.051)
Dist 45-59	-0.028**	-0.108*	-0.081*
	(0.044)	(0.061)	(0.064)
Dist over 60	-0.034**	-0.041**	-0.018*
	(0.038)	(0.056)	(0.052)
Observations	3,923	1,975	1,947

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

However, the second condition (non-correlation with the residuals of the labour force participation equation) cannot be tested empirically, thus the choice of a valid instrument largely depends on intuition and economic reasoning. We believe that there are intuitive arguments making distance to the nearest welfare office an important predictor of receiving disability benefits. Firstly, we argue that individuals who apply for disability benefits are likely to come from lower income quintiles, which affect their access of transport fares to the welfare office. As a result if the welfare office is located far from the applicant, the high transport costs ultimately reduce the likelihood of applying for the benefits by potential applicants. Some critics may argue that transport fares may be provided by other family members. Research has shown that the likelihood of members of a household with a potential social grant beneficiary to be unemployed is very high (Woolard & Leibbrandt 2010), thus the family may not be a valid source for transport fares. Additionally, the likelihood of receiving disability benefits should be high among individuals who are medically unfit to engage in any economic activity. Travelling for long hours may further affect such persons' health thus are likely to visit the welfare office if the distance to the office is minimal.

5.5 Results for OLS and IV regressions

Table 3 reports extracts of OLS and IV regressions results respectively. The full results for both specifications are reported in the appendix. In both specifications, estimation is separately done for the full sample, males and females respectively. The average effect of receiving disability benefits on labour force participation (ATT) was captured by disability grant dummy in an OLS regression, whilst in IV, ATT was estimated using a two stage least squares.

Using OLS regressions, we find that receipt of disability benefits reduces the probability of participating in the labour force by 22.3 percent for the full sample regression. When the sample is restricted to males only, the disincentive effect marginally declines to 21.6 percent, whilst restricting the sample to females only yields a marginal effect that is virtually similar to the full sample case.

Table 3: Estimation Results (marginal effects) for OLS and IV

	OLS			IV		
	Full Sample	Males	Females	Full Sample	Males	Females
Variable	(1)	(2)	(3)	(4)	(5)	ATT
Disability Grant (ATT)	-0.223***	-0.216***	-0.223***	-0.467***	-0.414*	-0.391
	(0.023)	(0.033)	(0.031)	(0.263)	(0.481)	(0.304)
Observations	2,398	1,254	1,141	2,398	1,254	1,141

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

When we instrument for individual participation in the DGP, we observe that enrolled individuals are more likely to withdraw from the labour force than was reported in OLS regressions. Specifically, the marginal effect of receiving disability benefits on the probability of withdrawing from the labour market is 46.7 percent for the full sample, more than 20 percent higher than was reported in OLS regression. The effect is lower for both males and females but still higher than the OLS respective effects, although not statistically significant for females. Despite the fact that our instrument passed the under-identification and weak instrumentation tests, the discrepancy of these results casts a doubt on the validity of our outcomes especially when our sample is restricted to males and females respectively. This raises the issue of the relevancy of the instrument used.

5.6 Robustness Check: The Evaluation Problem

The OLS and IV techniques assume that DG effect is uniform across the distribution of covariates and is adequately captured by the coefficient of a DG dummy. Nonetheless, economic theory provides no justification for such a linear restriction which brings a major drawback. We therefore complement our OLS and IV analyses with a non-parametric propensity score matching approach following the works of (Caliendo & Kopeinig 2008, Dehejia 2005, Dehejia & Wahba 2002, Smith & E Todd 2005, Heckman, Ichimura & Todd 1997, Rosenbaum & Rubin 1983, Rosenbaum & Rubin 1983).

Propensity score matching is implemented in two steps. Firstly, a probability model is estimated to calculate the probability (or propensity scores) of receiving disability benefits for each observation. In the second step, each recipient is matched to a non-recipient with similar propensity score values, in order to estimate the average treatment effect for the treated (ATT). Various matching methods have been developed to match recipients with non-recipients of similar propensity scores. Asymptotically, all matching methods should yield similar results. However, in practice, there are trade-offs in terms of bias and efficiency with each method(Caliendo & Kopeinig 2008). In this study, we use nearest neighbour, radius, local linear regression, kernel, and stratification based matching procedures.

Following (Rosenbaum & Rubin 1983), consider a random sample n of $18-60$ year old individuals with disabilities drawn from a sample of population of size N where $n_i < N$. N is thus the size of the admissible population. Each person within the sample is exposed to a binary treatment $D_i \in \{1, 0\}$; $D_i = 1$ if the person is enrolled in the DGP (treated) and $D_i = 0$ if the person does not receive disability benefits (control). Participants from both control and treated group have each a vector of pretreatment characteristics;

$$X_i = [X_{i,1}, X_{i,2}, ..., X_{i,k}] \tag{15}$$

with $k > 1$ and $i \in \{1, 2, ..., n\}$. The pretreatment characteristics include vocational factors like age, gender, marital status, household composition, provincial dummies as well as educational attainment levels. Let $\phi_{X|D=1}$ and $\phi_{X|D=2}$ represent the densities of these covariates in the treatment and control population respectively. $Y_i(W_i)$ is assumed to denote the pair of potential labour market participation outcomes that individual i attains if they are exposed to the treatment and vice-versa. The labour force participation status of each individual is thus;

$$Y_i = LFP_i = Y_i\left(1\right) D_i + \left(1 - D_i\right) Y_1\left(0\right) \tag{16}$$

From (16) it is apparent an individual can not be observed in either states at a time $i.e$ that is both participating and not participating in the labour market [2]. However for each individual we can simultaneously observe D, Y_i and X_i.

For each unit, the unobserved treatment effect θ is defined as;

$$\theta_i = Y_i(1) - Y_i(0) \tag{17}$$

5.6.1 Identification

For the purposes of this study, we are interested in measuring the probability of labour force participation for people who have been treated. This has traditionally been defined as the Average Treatment Effect on the Treated (ATT);

$$\theta \quad = \quad \underbrace{E\left[Y\left(1\right)|D=1\right]}_{identified} - \underbrace{E\left[Y\left(0\right)|D=1\right]}_{counterfactual} \tag{18}$$

The first part of (18) is easily estimable from the data. The second part $E\left[Y\left(0\right)|D=1\right]$

[2]It is possible to observe an individual in either states if one is using longitudinal data and the treatment is only administered some time after observation of the sample had started.

is however not identified as it is not possible to observe an individual receiving DG on one hand and on the other not receiving the DG. The only information available about $Y(0)$ is in the admissible population not exposed to the treatment. Identification of this part entails using propensity score matching The closer the propensity score, the better the match. It is crucial to ensure that the people who are selected into the control group are not systematically different from the treated individuals otherwise the identification process will be exposed to selection bias. We therefore need four crucial assumptions for identification.

5.6.2 Assumptions

5.6.3 Conditional Independence Assumption

The conditional independence assumption,

$$Y(0) \perp D|X \tag{19}$$

requires that conditioning on treatment the potential outcomes of the treated and non treated groups are similar. This assumption is valid insofar as the unobservables are unrelated to the probability of receiving the DG once one has conditioned on the relevant observable individual attributes. That is the set of $X's$ should contain all the variables that jointly influence labour force participation with no-treatment as well as the selection into treatment. Selection on unobservables is thus ignorable.

5.6.4 Stable Unit Treatment Value Assumption

We also require that the potential labour market participating outcome of a participant should be unaffected by the particular assignment of treatments to the other persons. This rules out interference of outcomes among individuals and non-identical versions of treatment

5.6.5 Exogeneity

$$X = X(1) = X(0) \tag{20}$$

Treatment should not have a causal impact on X, otherwise conditioning is partly on the effect. If violated the average treatment effects θ is still identified but can not be considered as causal.

5.6.6 Common Support Condition

$$0 < p(x) < 1, \forall x \in X \tag{21}$$

Expression (21) is the propensity score denoted

$$P(\text{Disability Grant}|X) \equiv p(x) \tag{22}$$

is the probability that an individual with disabilities receives the DG conditional on the corresponding vector of covariates (X)[3].

The propensity score provides a way of comparing those who are treated against those who are not treated in the sample. It is a measure of proximity between sample units and provides a way of summarizing all the information on the covariates set X into a single dimension vector so that comparison between units can be done on a probability level. When the propensity score is similar between a DG recipient and a non-recipient, we say that the outcome of interest from the non-recipent individual can serve as the 'counterfactual' outcome that the recipient would have had in the event of not receiving disability benefits. Once each recipient is matched to a non-recipient, the matching procedure goes on to compare average outcomes between recipients and non-recipients.

5.7 Empirical Strategy

The empirical strategy to evaluate the effect of the disability benefits on labour force participation relies on matching methods. The key issue upon which validity of results

[3] These are not the same Xs as would be selected if we were running a standard instrumental variables (IV) regression; in that case we would want Xs correlated with receipt of disability grant but not related with labour market status.

rest is the choice of a comparison.

5.8 Estimating Propensity Scores

We first estimate the propensity scores using a logit model. The dependent variable is the DG receipt dummy. The choice of the controls is based on the literature that high levels of education have a strong bearing on individual asset accumulation and that in turn depletes the likelihood of receiving disability benefits. Vocational factors such as age, marital status, population group as well as provincial dummies also affect selection into receiving disability grant. The distance from the social welfare influences one's decision in deciding to apply for the grant. Some communities are not easily accessible by public transport such that the transport costs that an individual incurs in the process of applying for the grant may act as a disincentive. We therefore included all these factors as control variables in estimating the propensity scores.

Table 4 presents the marginal effects of a logit estimation of the determinants of receiving the DG. The estimates show that several variables are statistically significantly associated with receipt of DG. Relative to Africans, Coloureds with disabilities are significantly likely to receive disability benefits, whilst opposite effects are observed for Asians and Whites albeit with statistically insignificant values. Restricting the sample males and females respectively yields statistically insignificant race effect on receipt of disability grant. Age is positively related with DG receipt for both males and females: older individuals have a higher likelihood of receiving the DG than younger individuals (18-24 years).

Table 4: Sensitivity of disability grant receipt to vocational factors (marginal effects of logit estimates)

Variable	All individuals with disabilities (1)	Males with disabilities (2)	Females with disabilities (3)
Coloured	0.072*	0.075	0.070
	(0.040)	(0.053)	(0.061)
Asian	-0.030	0.082	-0.104
	(0.091)	(0.125)	(0.125)
White	-0.003	0.005	-0.033
	(0.063)	(0.083)	(0.100)
Age 24-34 years	0.110***	0.111**	0.111*
	(0.037)	(0.048)	(0.059)
Age 35-44 years	0.165***	0.188***	0.148***
	(0.035)	(0.045)	(0.057)

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Table 4 – *Continued from previous page*

Variable	All individuals with disabilities (1)	Males with disabilities (2)	Females with disabilities (3)
Age 45-54 years	0.212***	0.218***	0.210***
	(0.036)	(0.047)	(0.059)
Age 55-60 years	0.168***	0.190***	0.158**
	(0.040)	(0.052)	(0.064)
Married	-0.047	-0.058	-0.044
	(0.031)	(0.046)	(0.043)
Cohabit	-0.041	-0.037	-0.055
	(0.041)	(0.057)	(0.061)
Widowed	-0.003	-0.048	0.030
	(0.045)	(0.088)	(0.056)
Divorced	-0.053	-0.116	0.002
	(0.054)	(0.081)	(0.074)
Primary	-0.090**	-0.065	-0.117**
	(0.037)	(0.053)	(0.053)
Secondary	-0.071	-0.013	-0.121*
	(0.047)	(0.066)	(0.068)
Matric	-0.105*	-0.075	-0.140
	(0.058)	(0.080)	(0.086)
Diploma	-0.420***	-0.211	-0.572***
	(0.068)	(0.129)	(0.031)
Degree	-0.269*	-0.263	-0.227
	(0.150)	(0.194)	(0.283)
Can read	0.027	0.153	-0.029
	(0.110)	(0.162)	(0.160)
Can write	-0.068	-0.236*	0.044
	(0.107)	(0.141)	(0.160)
Eastern Cape	0.236***	0.177**	0.294***
	(0.046)	(0.071)	(0.060)
Northern Cape	0.110*	0.056	0.160*
	(0.058)	(0.087)	(0.082)
Free State	0.173***	0.160**	0.183***
	(0.049)	(0.072)	(0.070)
KwaZulu Natal	0.149***	0.095	0.200***
	(0.052)	(0.079)	(0.072)
North West	0.088	0.087	0.091
	(0.056)	(0.081)	(0.081)
Western Cape	0.222***	0.195***	0.248***
	(0.050)	(0.073)	(0.072)
Mpumalanga	0.107**	0.003	0.209***
	(0.053)	(0.084)	(0.066)
Limpo	0.209***	0.195***	0.209***
	(0.052)	(0.075)	(0.078)
Infants present	-0.022	0.004	-0.052
	(0.041)	(0.061)	(0.057)
Children 1-7years present	-0.005	0.050	-0.070*
	(0.026)	(0.034)	(0.040)
Children 8-15 years presnet	0.030	0.033	0.006
	(0.030)	(0.042)	(0.047)
Over 60 year old present	0.082***	0.097***	0.080**
	(0.025)	(0.035)	(0.037)
District unemployment rate	0.055	0.130	0.033
	(0.148)	(0.212)	(0.216)
District LFP	0.059	0.065	0.046

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Table 4 – *Continued from previous page*

Variable	All individuals with disabilities (1)	Males with disabilities (2)	Females with disabilities (3)
	(0.134)	(0.183)	(0.201)
Sight	-0.250***	-0.259***	-0.257***
	(0.033)	(0.047)	(0.048)
Hearing	-0.258***	-0.345***	-0.198***
	(0.038)	(0.055)	(0.053)
Speech	0.034	-0.002	0.040
	(0.058)	(0.080)	(0.087)
Mental	0.039	-0.001	0.079
	(0.031)	(0.041)	(0.049)
Emotional	0.072**	0.057	0.090*
	(0.034)	(0.048)	(0.050)
Dist 15-29 minutes	-0.025	-0.079*	0.026
	(0.033)	(0.047)	(0.049)
Dist 30-44 minutes	-0.040	-0.067	0.006
	(0.035)	(0.049)	(0.052)
Dist 45-59 minutes	-0.077*	-0.127**	-0.030
	(0.044)	(0.062)	(0.063)
Dist over 60 minutes	-0.079**	-0.067	-0.096
	(0.040)	(0.057)	(0.060)
Observations	2,398	1,254	1,144

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Marital status and presence of children in the household are not significantly associated with DG receipt for both males and females, whilst as expected; there is an inverse association between educational attainment and receipt of DG. Relative to individuals with no formal education, individuals with post-primary education are less likely to receive the DG. The effect appears to increase with each successive educational cohort for both males and females.

Barring the North West province, all other provinces have a higher probability of hosting DG recipients compared with Gauteng. Individuals with emotional disabilities have a strong chance of receiving the DG relative to individuals with physical disabilities, at the same time as individuals with sight and hearing disabilities are less likely to receive the DG similarly compared with individuals with physical disabilities. Finally, the furthest an individual resides from the welfare office the less the probability of receiving disability benefits. This is especially true for males, whilst for females the effect is still negative but statistically insignificant.

5.9 Common Support Check

Before turning to the causal effects of the DG on labour supply, it is essential to check the region of common support and determine if we have enough overlap between the treated and control cases. Figure 8 provides a simple diagnostic on the data examined by plotting the histogram of the estimated propensity scores. A visual inspection of the density of distributions of the estimated propensity scores of recipients and non- recipients shows that the common support condition is satisfied.

The upper half (in red) shows the treated cases, while the control cases in blue are graphed below. Treated cases are restricted within propensity scores of 0.1 and 0.9 whilst control cases span the whole range of the propensity score, but above 0.9. Both treated and control cases are concentrated above propensity scores of 0.5. It thus appears we do not have a common support problem. It is nonetheless clear that there are fewer cases where few treated cases are similar to control cases. This should not present a challenge if matching is done with replacement as the few control cases that we do have with high propensity scores will be used over and over again as matches to the control cases.

5.10 Balance Checking

Propensity score methodology relies on balancing the observed distribution of covariates across DG recipients and non-recipients (Lee 2006). The balancing test is implemented after matching to check if differences in the covariates observed between DG recipients and non-recipients before matching were eliminated by matching. If no differences are observed after matching, the DG non-recipients are considered a plausible counterfactual. Of the several balancing tests explored in the literature, the mean absolute standardized bias (MASB) is the most widely used. A standardized difference of greater than 20 per cent should be considered too large and an indicator that the matching process has failed (Rosenbaum & Rubin 1983). If an affirmative result is achieved, the propensity score method becomes a reliable alternative to randomized clinical trials in terms of the bias introduced by using non-experimental data.

Table 5 presents balance check results before and after matching. Each row shows the mean of a variable for both treated and control groups. Further shown is the percentage bias (standardised difference between the mean of treated and control groups for the same variable. An additional column for the percentage reduction in bias (how much of the bias was eliminated by matching), is included for the matched cases. Balance is achieved if the p-value for the difference in treated and control means is not statistically significant for all variables. The results show that a couple variables failed the balance test pre-matching, but all the bias was eliminated through matching.

Table 5: Balancing tests on all covariates before and after matching with propensity scores

	Unmatched				Matched				
	Mean		%	p	Mean		%	% red	p
Variable	Treated	Control	bias	value	Treated	Control	bias	bias	value
Race									
African	0.766	0.794	-6.6	0.039	0.769	0.785	-3.9	40.8	0.139
Coloured	0.185	0.134	13.9	0.000	0.186	0.188	-0.4	97.2	0.923
Asian	0.016	0.017	-1.4	0.659	0.013	0.021	-6.7	-366.9	0.081
White	0.033	0.054	-10.5	0.001	0.030	0.029	0.3	96.7	0.911
Gender									
Male	0.555	0.465	18.1	0.000	0.534	0.515	3.8	78.8	0.309
Female	0.445	0.535	-18.1	0.000	0.465	0.484	-3.8	78.8	0.309
Age groups									
Age 18-24 years	0.095	0.167	-21.3	0.000	0.092	0.076	4.8	77.3	0.119
Age 25-34 years	0.176	0.194	-4.7	0.247	0.174	0.171	0.7	84.5	0.842
Age 35-44 years	0.255	0.233	5.1	0.212	0.254	0.251	0.8	83.9	0.829
Age 45-54 years	0.308	0.248	13.4	0.001	0.311	0.302	2.1	84.6	0.596
Age 55-60 years	0.166	0.158	2.1	0.600	0.169	0.179	-2.7	-25.3	0.487
Marital Status									
Single	0.572	0.455	23.5	0.000	0.556	0.530	5.3	77.5	0.163
Married	0.230	0.256	-6.3	0.053	0.230	0.235	-1.2	81.6	0.755
Cohabit	0.073	0.057	6.7	0.038	0.079	0.069	3.7	43.8	0.350
Widowed	0.083	0.193	-32.2	0.000	0.088	0.091	-1.0	96.8	0.742
Divorced	0.042	0.039	1.9	0.560	0.047	0.053	-2.9	-53.1	0.491
Educational Attainment									
No education	0.302	0.309	-1.4	0.657	0.277	0.311	-7.4	-409.4	0.148
Primary	0.471	0.474	-0.6	0.862	0.474	0.464	2.0	-250.4	0.598
Secondary	0.164	0.131	9.3	0.004	0.179	0.186	-2.0	78.4	0.626
Matric	0.055	0.055	-0.2	0.942	0.062	0.054	3.4	-1333.5	0.375
Diploma	0.005	0.023	-14.5	0.000	0.006	0.006	0.6	95.8	0.808
Degree	0.002	0.008	-7.8	0.021	0.003	0.005	-2.9	62.5	0.365
Literacy									
Can read	0.600	0.563	7.5	0.021	0.627	0.612	3.0	59.6	0.416
Can write	0.593	0.561	6.5	0.043	0.621	0.608	2.6	60.6	0.487
Province									
Gauteng	0.044	0.079	-14.6	0.000	0.096	0.038	0.6	96.0	0.846
Eastern Cape	0.179	0.131	13.2	0.000	0.180	0.168	3.3	74.8	0.399
Norther Cape	0.073	0.085	-4.4	0.172	0.076	0.071	1.8	58.6	0.613
Free State	0.085	0.092	-2.4	0.466	0.089	0.077	4.0	-69.0	0.275
KwaZulu Natal	0.257	0.250	1.4	0.655	0.247	0.259	-2.9	-103.4	0.436
North West	0.093	0.120	-9.0	0.006	0.096	0.111	-4.6	48.6	0.217
Western Cape	0.117	0.078	13.2	0.000	0.117	0.123	-1.9	85.5	0.643
Mpumalanga	0.072	0.098	-9.2	0.005	0.078	0.073	1.8	80.6	0.618
Limpopo	0.079	0.066	5.2	0.103	0.078	0.084	-2.5	53.0	0.535
Child status									
No children	0.333	0.338	-1.1	0.731	0.351	0.385	-7.3	-561.8	0.113
Infants present	0.084	0.081	0.8	0.806	0.082	0.101	-7.0	-779.2	0.078
Children 1-7 years present	0.380	0.388	-1.6	0.628	0.369	0.335	7.0	-347.5	0.059
Children 8-15 years present	0.202	0.192	2.7	0.406	0.198	0.199	-0.4	86.7	0.925
Pensioner									
Over 60 year old present	0.338	0.512	-35.7	0.000	0.291	0.285	1.2	96.7	0.740
Local Labour mkt conditions									
District unemployment rate	0.250	0.247	4.0	0.216	0.249	0.247	2.5	38.1	0.528
District narrow LFP	0.519	0.522	-2.8	0.382	0.517	0.517	0.6	80.3	0.881
Disability									
Physical	0.485	0.389	19.5	0.000	0.500	0.533	-6.7	65.6	0.107
Sight	0.075	0.223	-42.6	0.000	0.076	0.068	2.2	94.7	0.423

Continued on next page

Table 5 – *Continued from previous page*

	Unmatched				Matched				
	Mean		%	p	Mean		%	% red	p
Variable	Treated	Control	bias	value	Treated	Control	bias	bias	value
Hearing	0.053	0.173	-38.5	0.000	0.052	0.050	0.7	98.2	0.798
Speech	0.042	0.025	9.1	0.005	0.038	0.040	-0.8	91.3	0.846
Mental	0.214	0.118	26.2	0.000	0.200	0.172	7.7	70.6	0.053
Emotional	0.130	0.072	19.6	0.000	0.133	0.144	-3.8	80.7	0.383
Distance to public transport									
Dist 0-14	0.711	0.671	8.7	0.007	0.718	0.719	-0.2	98.2	0.967
Dist 15-29	0.316	0.314	0.5	0.875	0.313	0.332	-4.3	-740.5	0.260
Dist 30-44	0.253	0.237	3.7	0.252	0.250	0.259	-2.0	46.5	0.604
Dist 45-59	0.106	0.123	-5.2	0.110	0.107	0.120	-4.2	18.4	0.260
Dist over 60	0.154	0.177	-6.2	0.056	0.151	0.142	2.5	60.0	0.489

5.11 Results from Matching

Table 6 reports the estimates of the average labour supply effects of DG receipt estimated by nearest neighbour, radius, local linear regression, kernel and stratification matching algorithms. As a sensitivity analysis, the radius matching is implemented at three caliper sizes of 0.01, 0.02, and 0.05. All the analyses were based on implementation of common support, so that the distribution of DG recipients and non-recipients were located in the same domain. Bootstrap standard errors based on 400 replications are also reported.

Table 6: Average Treatment Effects Results

Matching Method	Bandwidth	Caliper	ATT	Standard Error	Observations Treated	Observations Controls
Nearest Neighbour			-0.213***	(0.026)	1418	563
Radius Matching		r=0.05	-0.200***	(0.018)	1418	965
		r=0.02	-0.197***	(0.018)	1415	965
		r=0.01	-0.197***	(0.020)	1414	963
Local Linear Regression	$b = 0.18$		-0.194***	(0.015)	1411	965
Kernel	$b = 0.14$		-0.197***	(0.016)	1418	965
Stratification			-0.192***	(0.017)	1418	965
Males						
Nearest Neighbour			-0.184***	(0.038)	759	292
Radius Matching		r=0.05	-0.196***	(0.028)	753	477
		r=0.02	-0.194***	(0.027)	759	483
		r=0.01	-0.198***	(0.028)	759	483
Local Linear Regression	$b = 0.18$		-0.196***	(0.020)	757	483
Kernel	$b = 0.14$		-0.197***	(0.026)	759	483
Stratification			-0.193***	(0.025)	759	483
Females						
Nearest Neighbour			-0.176***	(0.037)	659	263
Radius Matching		r=0.05	-0.199***	(0.028)	655	467
		r=0.02	-0.195***	(0.027)	658	473
		r=0.01	-0.192***	(0.027)	659	474
Local Linear Regression	$b = 0.18$		-0.193***	(0.022)	656	474
Kernel	$b = 0.14$		-0.187***	(0.029)	659	474
Stratification			-0.190***	(0.026)	659	474

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The outcome variable is narrow labour force participation. In order to further understand the labour supply impact of DG receipt on different recipients, we also examined the differential impact by dividing the sample into males and females. In each subset of the sample, the first row shows the results from nearest neighbour matching algorithm. The next three rows report the results from radius matching, with radii of 0.01, 0.02 and 0.05. Local linear regression and kernel based matching results are shown in the last two rows.

In all cases the results indicate that receipt of DG has a negative and significant effect on the probability of participating in the labour market. The decline in probability of labour force participation ranges from 19.2 to 21.3 percent for the full sample, 18.4 to

19.8 percent for males, and 17.6 to 19.9 percent for females. This is the average difference in probabilities of participating in the labour force for similar individuals that belong to different DG status (i.e. recipients and non-recipients). These results are consistent with the OLS results discussed earlier.

6 Conclusion

This paper investigated the impact of disability receipts on labour force participation in South Africa. The study utilised data from the 2007 wave of the General Household survey. The effect of disability benefits on labour force participation was estimated using OLS and IV regressions to control for observable variables and possible endogeneity of DGP participation. A variety of propensity score matching techniques were implemented to assess the robustness of the results. This helped in estimating the true effect of labour supply effect of disability benefits by controlling for the role of selection on enrolment to the DGP. Individuals with disabilities who receive disability benefits served as the treated group, while individuals with disabilities but not receiving disability benefits were the control cases.

Two main conclusions can be drawn from the results of this study on the impact of the DG on labour supply. Firstly, all results suggest that the DGP appears to have altered the labour market behaviour of working age individuals. OLS and PSM results suggest that individuals receiving disability rolls would have their probability of participating in the labour force increase by between 19.2 and 22.3 percent had they not been receiving the benefits, whilst the effect is larger for the IV regression. These results confirm a commonly held view among observers that the DGP promotes dependency by reducing labour supply.

Secondly, it is however almost impossible to proclaim this as the true labour supply effect of the DGP. A major concern arises from the inadequacy of the available data to control for the severity of disability of beneficiaries. Should there be differences in disability severity (health effect) between DG recipients and non-recipients, the effect of the DG on labour supply would be contaminated. Thus in as much as it is undisputable that the DGP does have some work disincentive effect, it is impossible to differentiate the reservation wage effect and the health effect from the observed overall effect.

Nonetheless, since inclusion and exclusion errors in disability tagging equally affect both the treated and control groups, it may not be entirely incorrect to assume that eligibility to the DGP satisfy the principles of randomisation. In this case the estimated coefficients in the paper will represent the true labour supply effects of the DGP. This may prove useful given some of the concerns among policy makers especially with regards to ensuring that people with disabilities are rehabilitated and eventually return to useful employment. Specifically, efforts to administer the DGP efficiently and effectively should focus on inventing a more systematic evaluation of potential DGP applicants, which would reduce the possibility of inclusion and exclusion errors.

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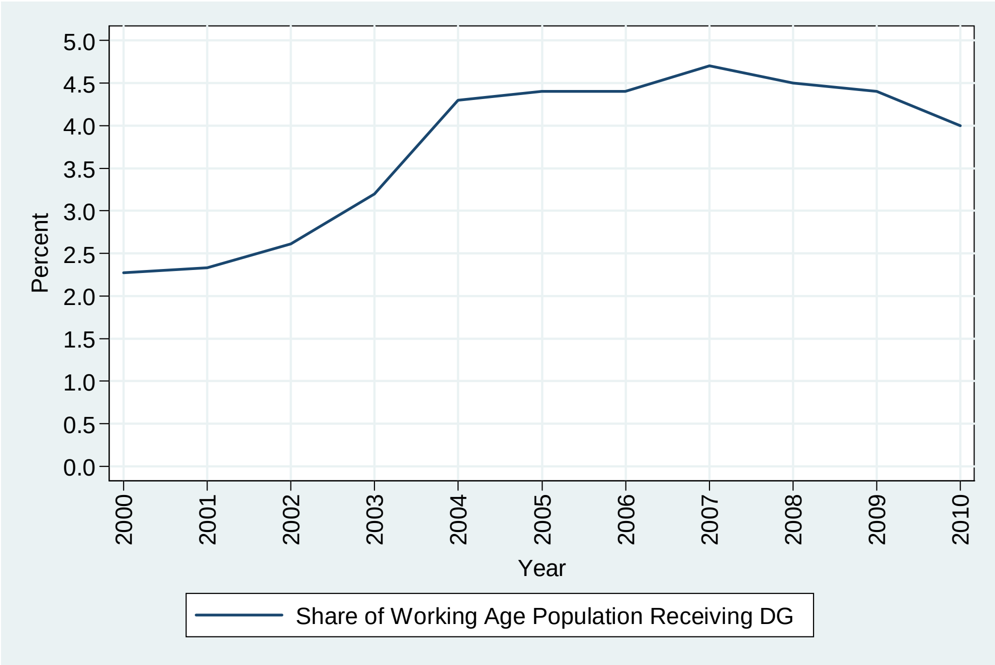
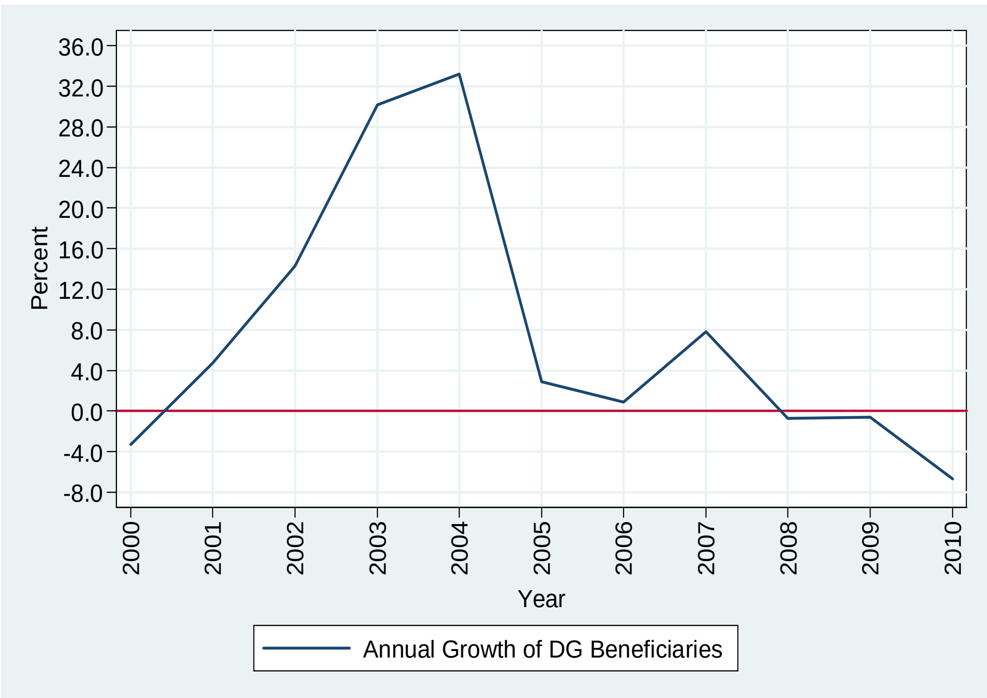
7 Appendix

Figure 1: Share of the working age population receiving disability benefits, 2000-2007



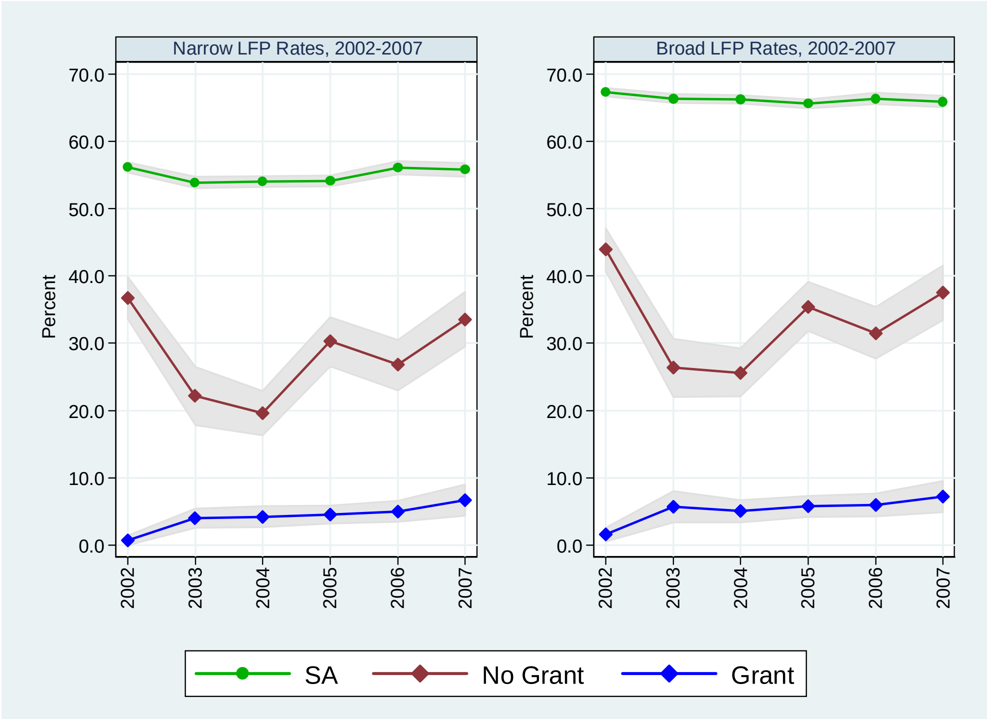
Source: National Treasury (Various years)

Figure 2: Annual growth in disability grant beneficiaries, 2002-2007



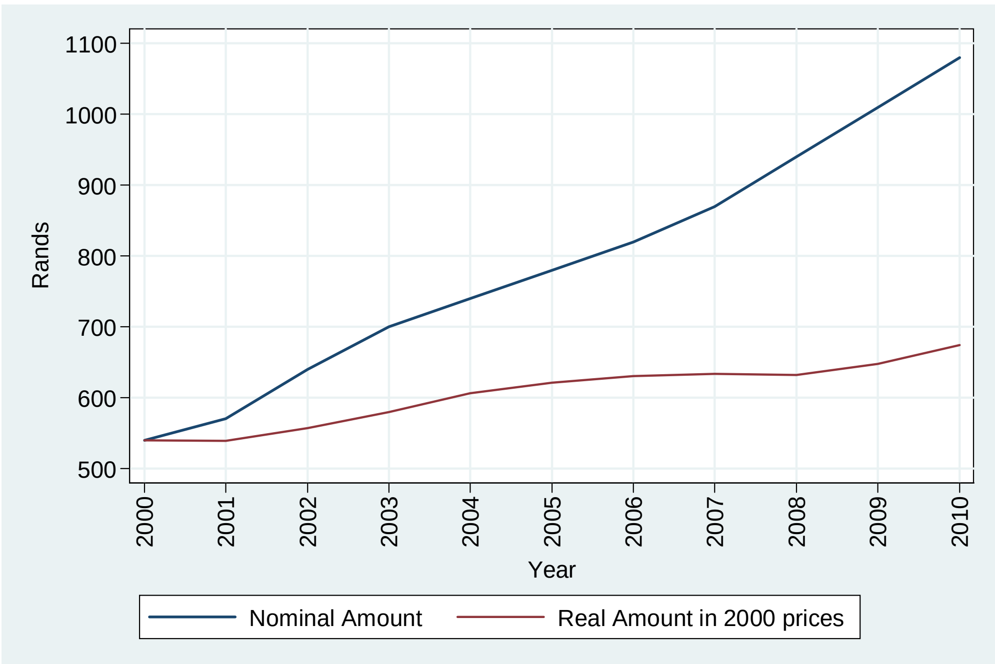
Source: National Treasury (Various years)

Figure 3: Labour force particibation rates by disability grant status, 2002-2007



Source: Author's calculations based on GHS, 2002-2007

Figure 4: Trends in disability grant maximum payouts, 2000-2010



Source: National Treasury (Various years)

Figure 5: Inclusion and exclusion errors as a proportion of the working age population, 2002-2008

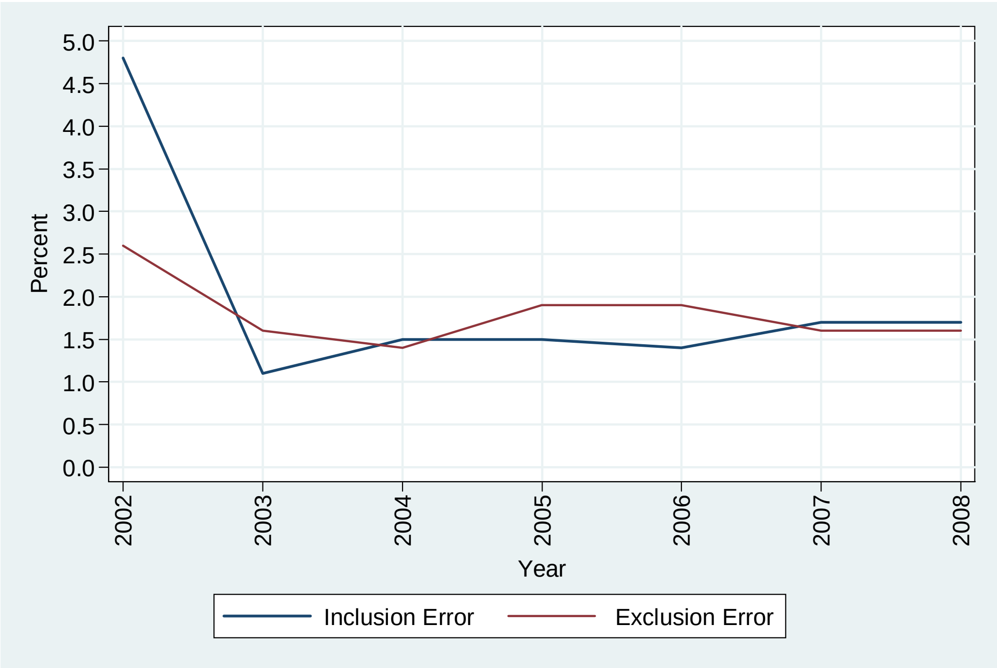
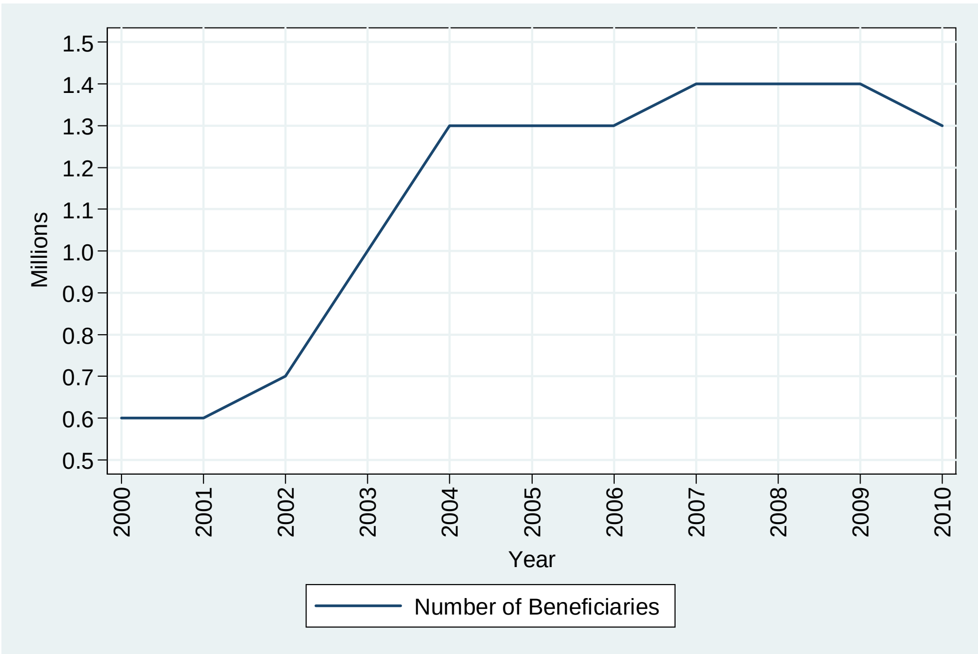
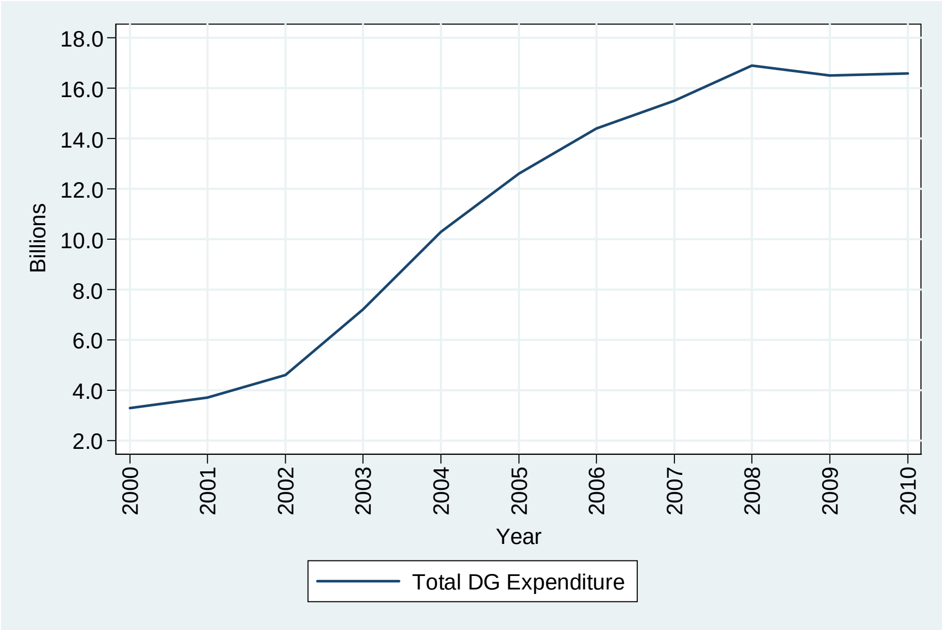


Figure 6: National trends in disability grant beneficiaries, 2000-2010



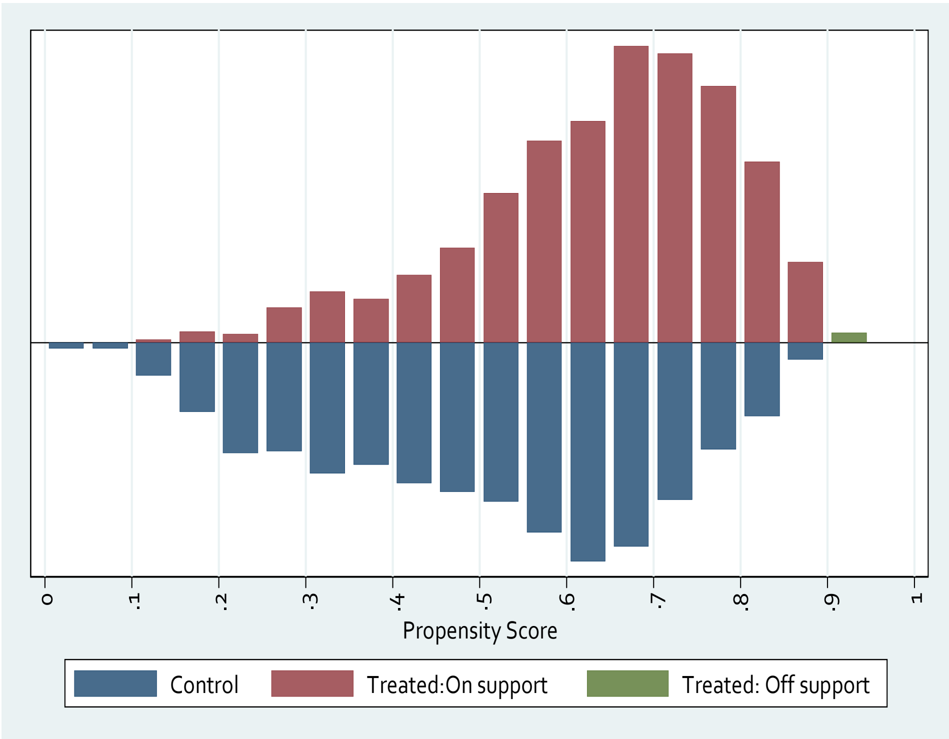
Source: National Treasury (Various years)

Figure 7: Total disability grant payments, 2000-2010



Source: National Treasury (Various years)

Figure 8: Histogram of estimated propensity scores



Note: "Treated: on support" shows the observations in the adoption group that have a suitable comparison. "Treated: off support" shows the observations in the adoption group that do not have a suitable comparison.

Table 7: Probit estimates (marginal effects) of labour force participation, 2007

	All observations with disabilities			Males with disabilities			Females with disabilities		
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Disability Grant	-0.234***	-0.252***	-0.219***	-0.271***	-0.272***	-0.226***	-0.197***	-0.231***	-0.207***
	(0.014)	(0.017)	(0.017)	(0.020)	(0.024)	(0.024)	(0.020)	(0.024)	(0.025)
Coloured		-0.043*	-0.034		-0.038	-0.027		-0.040	-0.032
		(0.023)	(0.024)		(0.031)	(0.032)		(0.036)	(0.037)
Asian		-0.063*	-0.065*		-0.041	-0.068		-0.092**	-0.075*
		(0.038)	(0.036)		(0.059)	(0.042)		(0.037)	(0.046)
White		-0.084***	-0.068***		-0.074**	-0.051		-0.103***	-0.094***
		(0.020)	(0.024)		(0.029)	(0.035)		(0.021)	(0.025)
Age 25-34		0.058*	0.062**		0.010	0.006		0.140**	0.162***
		(0.031)	(0.031)		(0.034)	(0.033)		(0.059)	(0.063)
Age 35-44		0.035	0.028		-0.010	-0.014		0.118**	0.113**
		(0.029)	(0.028)		(0.033)	(0.031)		(0.055)	(0.056)
Age 45-54		0.010	0.006		-0.047	-0.048		0.112**	0.112**
		(0.028)	(0.028)		(0.032)	(0.030)		(0.055)	(0.056)
Age 55-60		-0.026	-0.039		-0.068**	-0.080***		0.061	0.057
		(0.029)	(0.026)		(0.030)	(0.025)		(0.060)	(0.060)
Married		0.108***	0.087***		0.170***	0.141***		0.060*	0.049
		(0.025)	(0.024)		(0.041)	(0.040)		(0.031)	(0.031)
Cohabit		0.083**	0.055*		0.158***	0.113**		0.014	0.001
		(0.033)	(0.031)		(0.054)	(0.050)		(0.040)	(0.037)
Widowed		0.040	0.031		0.079	0.052		0.010	0.012
		(0.037)	(0.036)		(0.079)	(0.073)		(0.040)	(0.040)
Divorced		0.131***	0.133***		0.207**	0.208**		0.066	0.085
		(0.050)	(0.050)		(0.085)	(0.086)		(0.059)	(0.062)
Primary		0.020	0.018		0.030	0.022		0.001	0.004
		(0.027)	(0.026)		(0.037)	(0.036)		(0.039)	(0.039)
Secondary		0.044	0.027		0.012	-0.008		0.068	0.061
		(0.037)	(0.035)		(0.046)	(0.042)		(0.056)	(0.055)
Matric		0.163***	0.139**		0.108	0.079		0.216**	0.205**
		(0.058)	(0.057)		(0.073)	(0.068)		(0.092)	(0.092)
Diploma		0.248**	0.207**		0.280**	0.177		0.196	0.215
		(0.097)	(0.096)		(0.139)	(0.130)		(0.135)	(0.140)
Degree		0.307*	0.190		0.317	0.190		0.199	
		(0.158)	(0.150)		(0.197)	(0.177)		(0.275)	
Can read		0.008	-0.026		0.051	-0.021		-0.003	-0.003
		(0.074)	(0.082)		(0.093)	(0.113)		(0.105)	(0.106)
Can write		0.024	0.046		-0.035	0.037		0.052	0.042
		(0.071)	(0.070)		(0.110)	(0.099)		(0.092)	(0.095)
Eastern Cape		-0.038	-0.025		-0.044	-0.028		-0.064	-0.058
		(0.031)	(0.033)		(0.042)	(0.044)		(0.039)	(0.040)

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Table 7 – *Continued from previous page*

Variable	All observations with disabilities (1)	(2)	(3)	Males with disabilities (4)	(5)	(6)	Females with disabilities (7)	(8)	(9)
Northern Cape		0.069	0.040		0.078	0.036		0.022	0.006
		(0.050)	(0.046)		(0.071)	(0.062)		(0.064)	(0.060)
Free State		0.001	0.003		-0.070**	-0.064**		0.075	0.074
		(0.036)	(0.036)		(0.033)	(0.032)		(0.062)	(0.063)
KwaZulu Natal		-0.001	0.000		-0.022	-0.020		0.005	0.009
		(0.034)	(0.034)		(0.046)	(0.045)		(0.048)	(0.049)
North West		-0.039	-0.034		-0.054	-0.051		-0.037	-0.029
		(0.030)	(0.030)		(0.038)	(0.036)		(0.041)	(0.043)
Western Cape		-0.031	-0.026		-0.015	-0.015		-0.053	-0.040
		(0.035)	(0.035)		(0.053)	(0.051)		(0.043)	(0.046)
Mpumalanga		-0.011	-0.006		-0.018	-0.011		-0.014	-0.011
		(0.033)	(0.033)		(0.045)	(0.045)		(0.045)	(0.046)
Limpopo		-0.067**	-0.072***		-0.077**	-0.082***		-0.052	-0.056
		(0.030)	(0.027)		(0.036)	(0.029)		(0.047)	(0.045)
Infant present		-0.068***	-0.062***		-0.042	-0.030		-0.086***	-0.084***
		(0.019)	(0.019)		(0.033)	(0.034)		(0.023)	(0.023)
Children 1-7 years present		-0.034**	-0.027*		-0.038*	-0.032		-0.038	-0.030
		(0.016)	(0.016)		(0.021)	(0.021)		(0.024)	(0.025)
Children 8-15 years present		-0.015	-0.012		-0.027	-0.017		-0.008	-0.010
		(0.019)	(0.019)		(0.025)	(0.025)		(0.028)	(0.028)
Over 60 year old present		-0.041**	-0.033**		-0.039*	-0.028		-0.026	-0.023
		(0.016)	(0.016)		(0.023)	(0.023)		(0.024)	(0.024)
District unemployment rate		-0.115	-0.107		0.116	0.097		-0.361**	-0.327**
		(0.098)	(0.096)		(0.134)	(0.130)		(0.145)	(0.144)
District narrow LFP		0.189**	0.117		0.208*	0.134		0.107	0.042
		(0.090)	(0.089)		(0.120)	(0.116)		(0.133)	(0.134)
Sight			0.159***			0.179***			0.140***
			(0.031)			(0.045)			(0.044)
Hearing			0.107***			0.160***			0.065
			(0.032)			(0.053)			(0.040)
Speech			0.101*			0.090			0.111
			(0.052)			(0.070)			(0.078)
Mental			-0.080***			-0.086***			-0.059**
			(0.017)			(0.021)			(0.029)
Emotional			-0.005			0.000			-0.009
			(0.024)			(0.032)			(0.035)
Observations	2,862	2,435	2,398	1,508	1,274	1,254	1,354	1,161	1,141

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: First stage instrumental variable probit estimates (marginal effects) of disability grant take up, 2007

Variable	All observations (1)	Males (2)	Females (3)
Coloured	0.076*	0.080	0.071
	(0.039)	(0.053)	(0.061)
Asian	-0.026	0.070	-0.094
	(0.091)	(0.127)	(0.124)
White	0.014	0.027	-0.031
	(0.062)	(0.082)	(0.099)
25-34 years	0.107***	0.110**	0.112*
	(0.037)	(0.048)	(0.059)
35-44 years	0.165***	0.190***	0.151***
	(0.035)	(0.045)	(0.057)
45-54 years	0.211***	0.214***	0.213***
	(0.036)	(0.047)	(0.059)
55-60 years	0.166***	0.186***	0.158**
	(0.040)	(0.052)	(0.064)
Married	-0.041	-0.044	-0.042
	(0.031)	(0.046)	(0.043)
Cohabit	-0.036	-0.026	-0.051
	(0.041)	(0.057)	(0.061)
Widowed	-0.003	-0.035	0.027
	(0.045)	(0.088)	(0.056)
Divorced	-0.056	-0.111	-0.002
	(0.054)	(0.081)	(0.074)
Primary	-0.090**	-0.062	-0.117**
	(0.037)	(0.053)	(0.053)
Secondary	-0.073	-0.017	-0.120*
	(0.047)	(0.066)	(0.068)
Matric	-0.104*	-0.072	-0.138
	(0.058)	(0.080)	(0.086)
Diploma	-0.420***	-0.232*	-0.569***
	(0.068)	(0.127)	(0.033)
Degree	-0.265*	-0.280	-0.213
	(0.151)	(0.191)	(0.286)
Can read	0.042	0.152	0.000
	(0.111)	(0.162)	(0.162)
Can write	-0.080	-0.235*	0.017
	(0.107)	(0.141)	(0.161)
Eastern Cape	0.233***	0.170**	0.292***
	(0.046)	(0.072)	(0.060)
Northern Cape	0.119**	0.067	0.165**
	(0.058)	(0.086)	(0.082)
Free State	0.178***	0.160**	0.190***
	(0.049)	(0.072)	(0.069)
KwaZulu Natal	0.141***	0.091	0.188***
	(0.052)	(0.079)	(0.073)
North West	0.087	0.089	0.091
	(0.056)	(0.081)	(0.081)
Western Cape	0.231***	0.201***	0.254***
	(0.049)	(0.072)	(0.069)
Mpumalanga	0.105**	0.000	0.212***
	(0.053)	(0.084)	(0.066)
Limpopo	0.205***	0.192**	0.204***
	(0.053)	(0.075)	(0.079)

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Table 8 – *Continued from previous page*

Variable	All observations (1)	Males (2)	Females (3)
Infant present	-0.026	-0.006	-0.057
	(0.041)	(0.062)	(0.058)
Children 1-7 present	-0.007	0.044	-0.073*
	(0.026)	(0.035)	(0.040)
Children 8-15 present	0.024	0.030	-0.003
	(0.031)	(0.042)	(0.047)
Over 60 year old present	0.079***	0.094***	0.076**
	(0.025)	(0.035)	(0.036)
District unemployment rate	0.077	0.127	0.073
	(0.148)	(0.212)	(0.215)
District narrow LFP	0.056	0.026	0.084
	(0.133)	(0.182)	(0.199)
Sight	-0.251***	-0.258***	-0.256***
	(0.033)	(0.047)	(0.047)
Hearing	-0.257***	-0.344***	-0.192***
	(0.038)	(0.055)	(0.053)
Speech	0.042	0.015	0.047
	(0.057)	(0.079)	(0.087)
Mental	0.040	0.005	0.079
	(0.031)	(0.041)	(0.049)
Emotional	0.073**	0.056	0.094*
	(0.034)	(0.048)	(0.050)
Dist 15-29	-0.048*	-0.072*	-0.018
	(0.028)	(0.040)	(0.039)
Dist 30-44	-0.130***	-0.087	-0.184**
	(0.050)	(0.070)	(0.072)
Dist 45-59	-0.049	-0.022	-0.100
	(0.085)	(0.112)	(0.133)
Dist over 60	-0.050	-0.033	-0.064
	(0.080)	(0.113)	(0.118)
Observations	2,398	1,254	1,144

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Second-stage instrumental variable probit estimates (marginal effects) of disability grant take up, 2007

Variable	All observations (1)	Males (2)	Females (3)
Disability Grant	-0.437**	-0.608**	-0.207
	(0.216)	(0.288)	(0.327)
Coloured	-0.025	-0.005	-0.040
	(0.030)	(0.042)	(0.043)
Asian	-0.060	-0.067	-0.070
	(0.045)	(0.054)	(0.059)
White	-0.065**	-0.050	-0.095***
	(0.029)	(0.041)	(0.033)
25-34 years	0.086*	0.050	0.143*
	(0.044)	(0.053)	(0.077)

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Table 9 – *Continued from previous page*

Variable	All observations (1)	Males (2)	Females (3)
35-44 years	0.068	0.048	0.104
	(0.051)	(0.064)	(0.085)
45-54 years	0.055	0.026	0.106
	(0.059)	(0.075)	(0.098)
55-60 years	-0.009	-0.045	0.049
	(0.048)	(0.054)	(0.087)
Married	0.074***	0.118***	0.048
	(0.026)	(0.042)	(0.035)
Cohabit	0.043	0.089*	-0.002
	(0.032)	(0.050)	(0.042)
Widowed	0.029	0.067	0.004
	(0.036)	(0.077)	(0.041)
Divorced	0.115**	0.192**	0.071
	(0.051)	(0.085)	(0.064)
Primary	0.001	-0.014	0.011
	(0.033)	(0.046)	(0.047)
Secondary	0.012	-0.042	0.072
	(0.038)	(0.044)	(0.062)
Matric	0.107*	0.021	0.209**
	(0.059)	(0.065)	(0.100)
Diploma	0.076	-0.050	0.287
	(0.133)	(0.096)	(0.268)
Degree	0.109	0.057	
	(0.148)	(0.157)	
Can read	-0.032	-0.032	-0.026
	(0.083)	(0.111)	(0.118)
Can write	0.041	0.044	0.046
	(0.074)	(0.097)	(0.105)
Eastern Cape	0.021	0.081	-0.069
	(0.068)	(0.111)	(0.070)
Northern Cape	0.070	0.100	0.010
	(0.059)	(0.088)	(0.073)
Free State	0.043	-0.012	0.075
	(0.062)	(0.074)	(0.095)
KwaZulu Natal	0.028	0.039	0.005
	(0.049)	(0.072)	(0.067)
North West	-0.023	-0.037	-0.025
	(0.038)	(0.050)	(0.053)
Western Cape	0.023	0.088	-0.038
	(0.072)	(0.120)	(0.083)
Mpumalanga	0.014	0.051	-0.029
	(0.045)	(0.072)	(0.054)
Limpopo	-0.048	-0.037	-0.060
	(0.053)	(0.076)	(0.072)
Infant present	-0.070***	-0.038	-0.088***
	(0.021)	(0.036)	(0.028)
Children 1-7 years present	-0.033*	-0.049**	-0.020
	(0.017)	(0.022)	(0.027)
Children 8-15 years present	-0.007	-0.007	-0.008
	(0.022)	(0.030)	(0.032)
Over 60 year old present	-0.018	-0.009	-0.021
	(0.024)	(0.034)	(0.034)
Dsitrict unemployment rate	-0.104	0.125	-0.352**
	(0.105)	(0.143)	(0.155)

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Table 9 – *Continued from previous page*

Variable	All observations (1)	Males (2)	Females (3)
District narrow LFP	0.160	0.215	0.065
	(0.098)	(0.132)	(0.145)
Sight	0.087	0.049	0.146
	(0.071)	(0.088)	(0.117)
Hearing	0.041	0.043	0.058
	(0.067)	(0.093)	(0.105)
Speech	0.123**	0.123	0.118
	(0.055)	(0.077)	(0.082)
Mental	-0.078***	-0.081***	-0.061*
	(0.020)	(0.026)	(0.033)
Emotional	0.013	0.036	-0.010
	(0.031)	(0.045)	(0.042)
Observations	2,398	1,254	1,141

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1