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Abstract

The Child Support Grant (CSG) represents one of the major cash transfer implemented in South Africa to address children's vulnerability and household poverty. This paper provides an evaluation of the impact of the CSG on gender inequality by evaluating the effect of the programme on the employment status of adult members of beneficiary households. We use data from the 2008, 2010-2011 and 2012 National Income Dynamics Study and apply a fuzzy regression discontinuity design that exploits the expansion in eligibility due to a discontinous change in the age eligibility criterion. The analysis considers two source of heterogeneity in the impact of the CSG on labour market, i.e. gender and household members receiving the Old Age Pension social grant. In addition, the evaluation identifies differing effects by number of treated children in beneficiary households. Overall, this evaluation shows that the CSG had a negative effect on the probability of being employed of the beneficiary household members and increased gender inequality by strongly discouraging women's employment.

Keywords: Cash transfers, Regression discontinuity design, sub-Saharan Africa.
JEL code: I38, C33, O55.

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1. Introduction

The Child Support Grant (CSG) is a cash transfer introduced in South Africa in 1998 to support vulnerable children and their households and represents one of the main instrument of the national social protection strategy to address poverty and inequality (Barrientos *et al.*, 2014; Devereux, 2011; Niño-Zarazúa *et al.*, 2012). The grant is an unconditional monthly transfer given to up to six children per household, and is paid to their caregivers who, in most cases, are mothers and other women of the households (Agüero *et al.*, 2007).

The recipients are qualified on the basis of a means test with an income threshold amounting to ten times the monthly grant per child if they are single caregivers, and twenty if they are married[1]. In addition, at the start the program included children under 7 and then the eligible child age gradually increased. By 2010, eligibility underwent a sharp change: children born before January 1 1994 were eligible up to age 14 whereas those born after this date gained eligibility up to age 18 (Agüero *et al.*, 2007; Bor, 2013; Woolard *et al.*, 2011).

A number of studies evaluated the impact of the programme on differing dimensions of the well-being of children and their families and generally found positive results (d'Agostino *et al.*, 2016; Woolard *et al.*, 2011), but there is still little evidence on the effect of the CSG from the perspective of gender equality. This issue is of great importance because, despite the government's commitment to this objective, women discrimination, especially for African women, is a persistent probem in South Africa - for several reasons (Goldblatt, 2005; Patel and Hochfeld, 2011; Patel, 2012). In more detail, family disruption caused by apartheid economy still shapes African families' pattern: the majority of children live apart from their biological fathers and principally adult women provide care for childbearing and other duties (Budlender and Lund, 2011). In addition, women are increasingly working in paid employment, but they are overrepresented among low-wage workers and self-employed and differences in the employment rates between men and women are large and persistent (Posel and Rogan, 2009)[2].

Although the link between social grants and gender equality is complex and concerns several aspects, in the South African context, characterised by high rate of unemployment and earnings inequality, the most prominent issue is represented by the impact of social grants on labour market. In general, there are good reasons to believe that cash transfer programmes can affect household decision making, including labour supply. In the case of the CSG, most beneficiaries live in rural areas and face significant barriers that block their access to multiple markets, such as credit and labour (Kingdon and Knight, 2004). Hence CTs, when provided in a regular fashion, may help households overcome these obstacle (Asfaw *et al.*, 2014). In addition, in 2014 the CSG total amount per household ranged between R320 for households with one eligible child to R1,920 for households with six children. Given that in the same year the median monthly earning was R3,033 (R2,800 for the subgroup of black Africans, who are more likely to be poor and eligible for the programme) (StatSa (Statistics South Africa), 2015), the grant represents a significant income source for beneficiary families.

From a theoretical point of view, the impact of cash transfers targeting children on women's labour supply decision is ambiguous. The grant could disincentivise women's participation in the labour market by enhancing the value of time dedicated to housework activities, relative to time dedicated to paid work (i.e. income effect) (Asfaw et al. 2014). The grant can thus increase their reservation wage and create 'grant dependency' (Molyneux, 2009; Williams, 2007). The disincentive effect is even stronger when the programme selects beneficiary families with a stringent means test, making work unprofitable when earnings are close to the income threshold (Leibbrandt *et al.*, 2013; Williams, 2007). The income effect can also affect the labour supply decision of men, increasing their time dedicated to leisure, but it is expected that cultural norms and constraints of caring for children produce more pronounced effects on women. As a consequence, cash transfers may reinforce women's role as mothers with primary responsibility for family cares (Goldblatt, 2005; Molyneux, 2009; Patel, 2012).

[1]The grant was fixed at a level of R100 per month for each beneficiary child in 1998 and rose over years reaching R320 per month for each child in 2014. From 2008 onwards, the amount is adjusted every year to inflation(Agüero *et al.*, 2007; Woolard *et al.*, 2011).

[2]In 2014 the unemployment rate was 27.2% for women and 23,3% for men. According to the broad definition of unemployed, which includes the discouraged work-seekers, it was even higher, rising to 39.0% and 32.1%, for women and men respectively (StatSa (Statistics South Africa), 2015).

However, we may also expect opposite effects on women's labour market status: the grant improves their empowerment (Patel, 2012) and relax liquidity constraints, providing a financial support to reducing the burden of care and to enhancing job search or self-employment (Leibbrandt *et al.*, 2013; Patel *et al.*, 2013; Williams, 2007). Similarly, in the long-run the grant helps improving women's human capital, with a positive effect on their employment perspectives (Leibbrandt *et al.*, 2013).

There is limited empirical evidence on the impact of the CSG on women's employment and, generally, it showed positive results. Williams (2007) found that the program increased labour force participation and employment rates in grant-receiving households, with a stronger effect for women. Similarly, Eyal and Woolard (2011) found that the CSG significantly increased the probability of being employed of the recipient mothers. Both studies explain these positive effects on women employment with the fact that the grant helps funding child care costs, allowing mothers to entering the workplace. In contrast, there is robust evidence on the Old Age Pension (OAP), the other large-scale social grant implemented in South Africa, showing that pensions had mixed results on possible perverse labour market incentives (Ardington *et al.*, 2009; Devereux, 2013; Leibbrandt *et al.*, 2013; Williams, 2007; Banerjee *et al.*, 2008). However, the transmission channel of the impact in this case is different because the OAP targets people who generally are out of the labour force, and thus it influences only intra-household labour allocation, whereas the CSG provides cash to adult of working age, producing both a direct effect on recipients, and indirect effect on other household members (Williams, 2007).

It is also important to stress that, to our knowledge, no existing evaluation explicitly considers the effect on labour market outcomes of the joint receipt of the CSG and OAP by the same household. However, this effect must be rigorously taken into account as eligibility for the CSG depends on the income test which only includes the income of primary caregivers and her/his spouse (Woolard and Leibbrandt, 2013). Hence, it is possible that the CSG benefits are paid to household members with relatives receiving the OAP and that the cumulative impact of these transfers at household level amplifies the dependence effect on beneficiaries in working age.

This paper contributes to the previous literature by providing a rigorous evaluation of the impact of the CSG on the employment status of the adult household members to assess whether it produces a heterogeneous impact by gender in the labour market. Using the dataset provided by the National Income Dynamics Study (NIDS) covering 2008, 2010-2011 and 2012, we carry out a fuzzy Regression Discontinuity Design (RDD) that exploits the variation due to the extension in child age eligibility. This policy change created a discontinuous increase in the probability of being CSG beneficiary for children in the age interval 14-17 born after January 1 1994 and provides us the identification structure for the analysis. Following Calonico *et al.* (2014) and Cattaneo *et al.* (2015), we analyse the goodness of the identification structure through the non-parametric local polynomial (LP) estimator.

We then estimate the effect of the CSG by using the parametric instrumental variable (IV) approach. In more detail, we run IV regressions to estimate the local average treatment effects (LATE) (Lee, 2008; Lee and Lemieux, 2010; Jacob *et al.*, 2012). As more than one child (and up to six) can benefit from the CSG in the same household, we also evaluate how the effect changes when the number of beneficiary children increases, producing differing degree of exposure to the programme.

In addition, we consider two source of heterogeneity of treatment across units of observation, depending on gender and on the fact that effects change when members receiving the CSG and OAP live in the same household, increasing the total household income obtained from social grants. To capture heterogeneity across units due to gender and OAP social grants, we follow the approach proposed by Becker et al. (2013) to estimate the heterogeneous local average treatment effects (HLATE). Lastly, robustness analysis is applied to provide further checks on the internal and external validity of the fuzzy RDD by comparing the results obtained through the IV estimator with those obtained through the two-step propensity score (PS) procedure (van der Klaauw, 2002) and inverse distance weight (IDW) estimator[3].

Our main finding is that the CSG had a negative effect on the probability of being employed for the adult members of beneficiary households and this effect worsened for household members with more than one beneficiary child. In other words, this evaluation shows that the CSG created dependence of working-age adults on the transfers. In addition, the negative impact on the probability of being employed was

[3]For an extensive discussion on the use of the PS and IDW estimators, see d'Agostino *et al.* (2016)

especially strong for women and for members of households receiving both the CSG and OAP. Our analysis also shows that the reduction in the probability of being employed for both women and men only partially resulted in an increase of the probability of being searching unemployed whereas it was in large part balanced by an increase in the probability of being out of labour force (i.e., Not Economically Active, NEA). The increase in the probability of being in the out-of-labour-force state involved mainly women aged from 31 to 55 and men from 46 to 50, thereby affecting the potentially most productive persons in the total working age population. Overall, this evaluation shows that the CSG had a negative effect on employment opportunities of the beneficiary household members and increased gender inequality by strongly discouraging women's employment.

The paper is organised as follows: Section 2 introduces the dataset and descriptive statistics; Section 3 presents some preliminary analyses; Section 4 discusses the results and Section 5 shwos the robustness analysis. Section 6 concludes.

2. Data and descriptive statistics

As mentioned in Section 1, the CSG benefits are provided to eligible beneficiaries according to a means test and child age[4]. From January 1 2010, age eligibility was extended, so that children born after January 1 1994 were eligible until their 18th birthday, whereas those born before that date lost eligibility at 14. The discontinuity in the age eligibility criterion provides a clear-cut natural experiment to be carried out by applying a fuzzy RDD and looking at the causal effects of the CSG across birth cohorts.

The empirical analysis is based on the datased provided from the National Income Dynamic Study (NIDS) which was implemented by the South African Labour and Development Research Unit (SALDRU) of the University of Cape Town. The NIDS was available for the waves 2008, 2010-2011 and 2012, and allowed a face-to-face longitudinal survey of households resident in South Africa. Its aim was to follow a sample of household members and register changes in household compositions and migrations and several dimensions of well-being (e.g., incomes, expenditures, assets, access to social services, education, health, employment). The dataset also includes informations on the beneficiary households of the social grants provided by the government.

From the dataset we extract relevant informations related to the annual birth cohort of children born in the period 1990-2009, in a corresponding age range of 0-17 years and link this information to each adult of the household in the working age (from 15 to 64 years). We drop from the sample all the birth cohorts of children before 1990 since they are never eligible for the CSG and exclude the birth cohorts of 2010, 2011 and 2012 because the information on these cohorts is available only in the last waves. As the grant is given for each beneficiary child up to a maximum of six children, the identification has to account for differing degrees of exposure to the policy within the same household and for each individual. To account for these differences, we use the information on each treated child in its birth cohort for each adult in the beneficiary household. This procedure generates six dataset to be compared with the control group. However, to ensure an easy reading of the results, in the empirical analysis we aggregate the number of beneficiary children in four different categories: i) one treated child, ii) two treated children, iii) three and four treated children and iv) five or six treated children.

From the dataset we extract informations on several variables related to the labour market, and classify working age individuals in three states: employed, unemployed and not economically active (NEA). These states are the outcome variables of the impact evaluation. We use the narrow definition of unemployed workers, i.e. unemployed work seekers. Hence, NEA includes both the unemployed who are discouraged work seekers and people who, for other reasons, do not enter the labour force (Kingdon and Knight, 2006; StatSa (Statistics South Africa), 2015). This distinction is useful for our empirical analysis because allow us to test the hypothesis that social grants support job search vis-a-vis the hypothesis that they disincentives beneficiary adults engaging actively in the labour market, either by working or looking for work.

Appendix A reports some descriptive statistics for the three outcome variables and for the chosen covariates. The list of covariates includes gender, age, education of the working age individuals, along with

[4]For a detailed discussion on the progressive changes in these criteria, see d'Agostino *et al.* (2016)

(a) Employment

(b) Unemployment

(c) NEA

Figure 1: Outcome variables, by age and gender

household composition and household members receiving the OAP social grant. Districts and the provinces where individuals live are also included in the covariate list, but not reported in the Appendix.

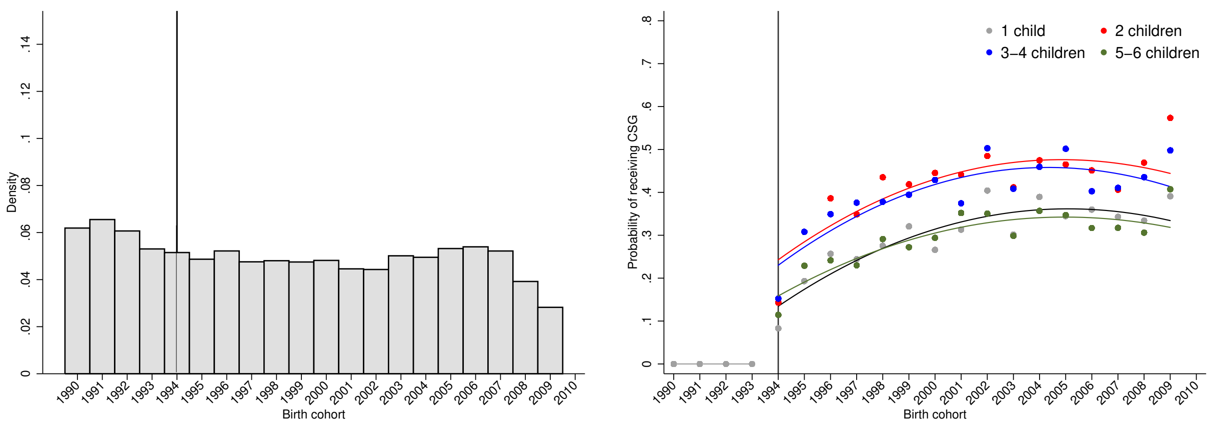
We conclude this Section by briefly outlining the behaviour of the outcome variables (probability of being employed, unemployed and NEA) disaggregated by age and gender. Figure 1, panel a, shows that the probability of being employed is markedly lower for women compared with men. The gap increases by age and becomes still more relevant for middle-age individuals. A similar behaviour is found when the probability of being NEA is considered, in the bottom panel. Conversely, the probability of being unemployed shows a similar behaviour for women and men.

3. Preliminary analyses

As a preliminary step, we present a falsification test which examines whether, in a local neighbourhood of the cutoff, the number of observations below the cutoff is significantly different from the number of observations above it. Figure 2, panel a, shows that we have approximately a similar density in the neighbourhood of the 1994 cutoff, even if this result changes away from it. In addition, we present a formal statistic which, under the null hypothesis, tests if the density of the assignment variable is continuous at the cutoff[5]. We find that the null hypothesis is satisfied (test-statistic 1.207, *p-value* 0.227).

[5]See Cattaneo *et al.* (2015).

Figure 2, panel b, shows the relationship between the assignment variable (birth cohort) and treatment status obtained with the LP estimator. To account for differing degree of exposure to the programme, we report four LP estimations for the cases in which the individual has one, two, three or four, and five or six beneficiary children. Children in birth cohorts outside the age eligibility for the CSG lay on the left of the cutoff, whereas children who are both in the treated and control groups lay on the right.

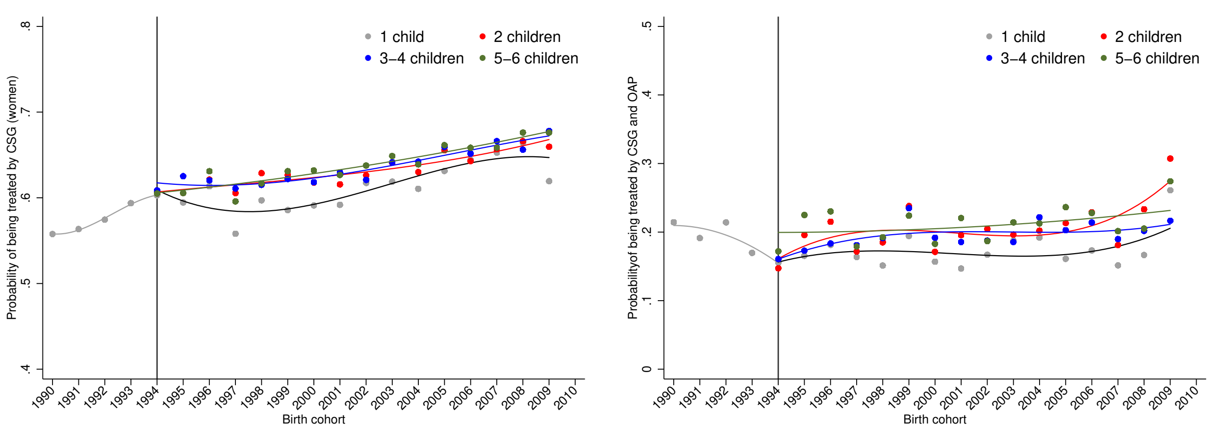


(a) Density by birth cohorts

(b) Probability of receiving CSG

Figure 2: Falsification tests on the LATE assumptions
Notes: Construction of evenly spaced bins in panel b follows Calonico *et al.* (2014).

The figure confirms the fuzzy nature of the RDD, showing that only 10% of individuals in the sample were involved in the CSG. More interestingly, a clear self-selection emerges among the beneficiary household members because the probability of entering the programme varies with the number of beneficiary children. This result suggests that we have to take into account the differing degrees of exposure to the programme in the empirical investigation.



(a) Gender

(b) OAP

Figure 3: Falsification tests on the HLATE assumption
Notes: Construction of evenly spaced bins follows Calonico *et al.* (2014).

To complete the preliminary analysis, Figure 3 plots the probability of being treated by the CSG for the two interaction variables identifying HLATE by gender and members of household that also receive one or more grants from the OAP. In line with Figure 2, we distinguish among different degrees of exposure to the CSG (i.e., number of beneficiary children in the household). As Figure 3 shows, we do not find any discontinuity when plotting the gender and OAP variables. This result supports the further assumption necessary to estimate HLATE, which requires the interaction variables to be continuous at the cutoff of the assignment variable (Becker *et al.*, 2013). The result is valid for each degree of exposure to the CSG, as showed by the coloured lines, hence this assumption holds. Furthermore, the falsification tests, reported in the figure, show also the balance of gender and OAP between treated and control groups. The same structure of falsification tests is also applied to inspect the balance of other covariates, as reported in Appendix B.

4. Results

Tables 1, 2 and 3 summarises the results obtained with parametric IV regressions. Each of these tables is organised horizontally in three blocks and vertically in five columns. The three blocks refer to second order polynomial specifications of the control function[6]: we first estimate the LATE and then two differing HLATE which include the gender and OAP interaction variables. The five columns present the results for the full sample (all individual treated by the programme) and for differing degrees of exposure to the CSG (individuals classified by number of treated children). In line with the previous figures, we classify individuals by one, two, three or four, and five or six treated children[7].

The parameters reported in the first block of each table can be interpreted in terms of the LATE, and the parameters in the two remaining blocks in terms of the HLATE. In more detail, by introducing the interaction term CSG x gender, we test the hypothesis that the impact of the CSG is different for men and women. In this case, the interaction term captures the heterogeneous effect on women of being treated by the CSG and the CSG parameter can be interpreted as the net effect on outcome variables for treated women, compared with all other units. Obviously, the same explanation can be used when the OAP is taken into account.

In all the blocks, we test for weak instruments and report first-stage F statistics and Wald statistics based on the Cragg and Donald (1993)and Kleibergen and Paap (2006) generalisation to non-independently and non-identically distributed errors, together with the $p-values$ (Bazzi and Clemens, 2013). In blocks 2 and 3 we report also an underidentification test based on the Kleibergen-Paap LM test statistic. In addition, all the specifications include the covariates reported in Appendix A, along with provincial[8] and time fixed effects, whereas the reported error terms are robust and clustered at the individual level to account for the violation of the i.i.d in the data.

Table 1 reports the estimated results when the probability of being employed is considered. From the first column of the upper block, the table shows that, when we consider the full sample, we find that the expansion of the CSG age eligibility criterion produced a negative variation of 7.8% in the probability of being employed, which is significant at less than 1% level. This impact significantly varies across the degrees of exposure to the CSG, as showed in the remaining four columns. When only one child is treated by the CSG, we find an effect of 2.6% on the probability of being employed, which is statistically significant at only 10% level. The impact increases when two beneficiary children and five or six beneficiary children are analysed. An intermediate result is found when the group with three or four children is analysed.

More interesting results emerge from the second block of Table 1, where the heterogeneity due to gender is analysed. The table shows that the interaction term (CSG X Gender) is always positive and statistically significant. When the full sample is taken into account, we find a strong decrease (19.6%) in the probability of being employed when the heterogeneity due to gender is considered, with a significant level less than 1%. This result is robust when compared with the results for the cases with two, and five or six treated children.

[6]Following the recent contributions by Gelman and co-authors (**??**), the use of high degree polynomials in the RDD can be misleading since results based on high order polynomial regressions are sensitive to the order of the polynomial. Further, global goodness of fit measures are not good measures for choosing the order optimally, since are not closely related to the research objective of causal inference. Following these su suggestions, we apply e a second order polynomial both in the first and second stage of the analysis.

[7]Following Becker *et al.* (2013), the CSG is instrumented using the fit a probit auxiliary regression linked to the annual birth cohort of each treated child in the household (Wooldridge, 2002).

[8]To account for differences in labour markets, we introduce provincial dummies, along with provincial linear and quadratic trends.

Table 1: Impact of CSG on Employment, by gender and OAP heterogeneity

	Full sample	Treated children			
		One	Two	Three or four	Five or six
CSG	-0.078 ***	-0.026 *	-0.069 ***	-0.039 **	-0.070 **
	(0.012)	(0.014)	(0.014)	(0.017)	(0.029)
Cragg-Donald F statistic	60512.904	23072.198	47831.364	49342.665	21342.053
Kleibergen-Paap F test statistic	14001.814	2,940.502	11562.524	14448.842	1,848.400
R^2	0.189	0.233	0.232	0.241	0.256
Adj. R^2	0.188	0.232	0.231	0.240	0.254
No. of observations	47,895	20,181	23,972	23,419	23,754
	Gender heterogeneity				
CSG	-0.196 ***	-0.147 ***	-0.199 ***	-0.127 ***	-0.222 ***
	(0.033)	(0.048)	(0.039)	(0.045)	(0.058)
CSG X Gender	0.070 ***	0.073 ***	0.077 ***	0.052 **	0.085 ***
	(0.019)	(0.027)	(0.022)	(0.025)	(0.028)
Gender (women)	-0.227 ***	-0.231 ***	-0.227 ***	-0.228 ***	-0.224 ***
	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)
Cragg-Donald F statistic	30458.956	11522.653	24000.260	24687.210	10652.769
Kleibergen-Paap F test statistic	6,944.982	1,404.633	5,501.775	7,003.405	927.670
Kleibergen-Paap LM test statistic	1,731.001	2,547.761	1,887.885	905.453	263.532
Adj. R^2	0.189	0.232	0.232	0.240	0.255
No. of observations	47,895	20,181	23,972	23,419	23,754
	OAP heterogeneity				
CSG	-0.095 ***	-0.026	-0.083 ***	-0.056 ***	-0.108 ***
	(0.013)	(0.018)	(0.015)	(0.019)	(0.032)
CSG X OAP	0.024 ***	-0.000	0.017 *	0.018 **	0.025 ***
	(0.009)	(0.026)	(0.010)	(0.009)	(0.009)
OAP	-0.037 ***	-0.026 ***	-0.031 ***	-0.031 ***	-0.032 ***
	(0.008)	(0.009)	(0.007)	(0.007)	(0.007)
Cragg-Donald F statistic	19081.594	1,761.750	11721.728	18079.336	10719.919
Kleibergen-Paap F test statistic	263.609	7.768	142.148	450.321	946.367
Kleibergen-Paap LM test statistic	119.995	40.384	155.511	161.102	269.640
Adj. R^2	0.189	0.232	0.231	0.240	0.255
No. of observations	47,895	20,181	23,972	23,419	23,754

Notes: In all blocks, dependent variable is the probability of being employed (see the list of the covariates in Appendix A). The polynomial functions are allowed to have different parameters to the left and right of the threshold. Robust and clustered standard errors are shown in brackets. For the second and third blocks, first-stage regressions are probit models. Asterisks: *p-value* levels (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$). Tests for weak and underidentification of the instrument F statistics and Wald statistics based on Cragg and Donald (1993) and Kleibergen and Paap (2006).

A less evident heterogeneity emerges in the bottom block of Table 1, that shows the interaction between the CSG and OAP. We find that for the full sample the interaction between the two social grants causes a reduction in the probability of being employed of 9.5% (p-value < 1%). In this case, significant results are obtained only for the subsamples with more than one treated child. Overall, Table 1 shows that the CSG has a strong negative impact on employment, especially when heterogeneity due to gender is taken in account.

We now consider how the CSG affects the probability of beneficiary household members of being in the other two labour market state. i.e. the probability of being unemployed and not economically active (NEA). We recall that we are using the narrow definition of unemployment, which means that we consider the unemployed actively searching for a job, whereas the category NEA includes both non-searching unemployed and out-of-labour-force individuals. Our interest is to assess if the reduction in the probability of being employed results in an increase in searching unemployed or NEA. In the first case, one possible interpretation is that the CSG, on the one hand, discourages employment, but on the other hand it relaxes the liquidity constraints for the most deprived persons, thus increasing their probability of actively engaging in job search. In the second case, instead, the CSG definitely discourages labour market participation.

The first block of Table 2 shows that in the full sample the negative variation in the employment (7.8% in the first column of Table 1) is compensated by an increase in the population engaged in job search (6.8%, p-value < 1%). However, when considering the heterogeneity due to gender, this effect vanishes: we find that the reduction of 19.6% in employment (Table 1) is only partially offset by an increase in the probability of being searching unemployed (9.7%, p-value < 1%).

A similar situation is found when considering heterogeneity due to the OAP. The bottom block of the table shows that the reduction in the probability of being employed (9.5%, p-value < 1%) is only partially offset by a positive variation in the probability of being searching unemployed (5.3%, p-value < 1%). It is also interesting that introducing the interaction between the CSG and the OAP markedly reduces the probability of being (searching) unemployed, with strong heterogeneity effects in the differing degrees of exposure to the CSG, as showed by the remaining four columns.

Finally, Table 3, analyses the impact of the CSG on the probability of being NEA. In line with expec-

Table 2: Impact of CSG on Unemployment, by gender and OAP heterogeneity

	Full sample	Treated children			
		One	Two	Three or four	Five or six
CSG	0.068 ***	0.037 ***	0.060 ***	0.065 ***	0.084 ***
	(0.010)	(0.011)	(0.011)	(0.014)	(0.023)
Cragg-Donald F statistic	63564.536	24774.411	50221.481	52013.953	24271.165
Kleibergen-Paap F test statistic	14097.626	2,887.357	11738.602	13769.160	3,178.525
Adj. R^2	0.075	0.074	0.077	0.082	0.084
No. of observations	50,176	21,646	25,562	24,932	21,447
	Gender heterogeneity				
CSG	0.097 ***	0.026	0.058 **	0.112 ***	0.177 **
	(0.024)	(0.031)	(0.028)	(0.031)	(0.079)
CSG X Gender	-0.018 *	0.007	0.001	-0.025	-0.011
	(0.010)	(0.018)	(0.016)	(0.016)	(0.034)
Gender (women)	0.027 ***	0.020 **	0.021 ***	0.022 ***	0.019 ***
	(0.009)	(0.008)	(0.008)	(0.008)	(0.007)
Cragg-Donald F statistic	32017.488	12354.431	25223.096	27155.017	3,563.369
Kleibergen-Paap F test statistic	7,015.635	1,258.361	5,651.037	5,143.254	157.173
Kleibergen-Paap LM test statistic	1,764.663	2,620.523	1,979.093	784.380	53.915
Adj. R^2	0.074	0.074	0.077	0.082	0.075
No. of observations	50,176	21,646	25,562	30,650	19,505
	OAP heterogeneity				
CSG	0.053 ***	0.036 ***	0.046 ***	0.063 ***	0.118 **
	(0.010)	(0.014)	(0.012)	(0.015)	(0.050)
CSG X OAP	0.020 ***	0.002	0.017 **	0.006	0.020 **
	(0.007)	(0.023)	(0.008)	(0.006)	(0.009)
OAP	-0.015 **	-0.009	-0.011 **	-0.004	-0.013 **
	(0.006)	(0.007)	(0.005)	(0.005)	(0.005)
Cragg-Donald F statistic	18261.297	1,486.027	10518.202	20722.571	3,629.250
Kleibergen-Paap F test statistic	259.700	7.552	130.351	700.320	159.991
Kleibergen-Paap LM test statistic	127.859	37.288	162.654	142.627	54.909
Adj. R^2	0.075	0.074	0.078	0.082	0.078
No. of observations	50,176	21,646	25,562	30,650	19,505

Notes: In all blocks, dependent variable is the probability of being unemployed (see the list of the covariates in Appendix). The polynomial functions are allowed to have different parameters to the left and right of the threshold. Robust and clustered standard errors are shown in brackets. For the second and third blocks, first-stage regressions are probit models. Asterisks: *p-value* levels (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$). Tests for weak and underidentification of the instrument F statistics and Wald statistics based on Cragg and Donald (1993) and Kleibergen and Paap (2006).

tations, the first block of the table does not show any significant coefficient, suggesting that the reduction in the employment caused by the CSG is fully compensated by an increase in the unemployed engaged in job search. On the contrary, when gender heterogeneity is taken into account (middle block of Table 3), a positive and statistically significant impact of the CSG on the probability of being NEA is found; this effect is higher when considering the heterogeneous exposure of women to the CSG (6.4%, p-value < 5%) compared with the LATE estimate. A similar result is found when the interaction between the CSG and OAP is considered, with a higher probability of being NEA (4.2%, p-value < 1%) compared with the previous estimate.

To complete the analysis, Figure 4 shows the marginal effects of the GSC on the three outcome variables (probability of being employed, unemployed, NEA) and the corresponding confidence interval for differing age cohorts, distinguishing between men and women subpopulations. To calculate the marginal effects, we used the full-sample estimates reported in Table 1, 2 and 3. For a quick interpretation of the results, we mark with a black triangle the marginal effects not statistically significant (i.e., p-value> 10%).

A comparison among the three plots, shows that the effects of the exposure to the CSG are never statistically significant for young individuals (people under 25 years). This result is not surprising since, in this age range, the proportion of grant's recipients is low. A similar result is found for the subpopulation including the oldest individuals. In more detail, Figure 4, panel a, shows that the reduction in the probability of being employed due to the CSG is much stronger for women compared with men, especially those in the age range from 36 to 55, with the highest peak in the age range from 41 to 50.

When the probability of being unemployed is analysed (Figure 4, panel b), we find a symmetrical behaviour of the plot but the increase in the probability of being a searching unemployed only partially offsets the reduction in employment.

The bottom panel of the figure shows the marginal effect of the CSG on the probability of being NEA. In this case, we find significant results for the age range from 31 to 55 when the women subpopulation is

Table 3: Impact of CSG on NEA, by gender and OAP heterogeneity

	Full-sample	Treated children			
		One	Two	Three or four	Five or six
CSG	0.018	0.005	0.017	0.013	0.017
	(0.012)	(0.014)	(0.012)	(0.012)	(0.012)
Cragg-Donald F statistic	63564.536	24774.411	42157.906	55040.331	60761.746
Kleibergen-Paap F test statistic	14097.626	2,887.357	9,076.951	14182.724	14999.054
Adj. R^2	0.170	0.178	0.172	0.174	0.171
No. of observations	50,176	21,646	31,479	40,682	46,400
	Gender heterogeneity				
CSG	0.064 **	0.073 *	0.083 ***	0.053 **	0.063 **
	(0.028)	(0.041)	(0.028)	(0.027)	(0.027)
CSG X Gender	-0.027 *	-0.041 *	-0.040 **	-0.024	-0.027 *
	(0.016)	(0.025)	(0.017)	(0.016)	(0.016)
Gender (women)	0.179 ***	0.187 ***	0.185 ***	0.179 ***	0.179 ***
	(0.011)	(0.010)	(0.010)	(0.011)	(0.011)
Cragg-Donald F statistic	32017.488	12354.431	21197.117	27665.607	30577.771
Kleibergen-Paap F test statistic	7,015.635	1,258.361	4,508.248	7,013.871	7,438.495
Kleibergen-Paap LM test statistic	1,764.663	2,620.523	2,214.440	1,809.332	1,728.419
Adj. R^2	0.170	0.178	0.172	0.174	0.171
No. of observations	50,176	21,646	31,479	40,682	46,400
	OAP heterogeneity				
CSG	0.042 ***	0.001	0.046 ***	0.013	0.078 **
	(0.013)	(0.019)	(0.015)	(0.020)	(0.036)
CSG X OAP	-0.034 ***	0.010	-0.027 **	-0.013	-0.035 ***
	(0.010)	(0.033)	(0.011)	(0.010)	(0.010)
OAP	0.040 ***	0.029 ***	0.036 ***	0.028 ***	0.034 ***
	(0.008)	(0.010)	(0.007)	(0.007)	(0.007)
Cragg-Donald F statistic	18261.297	1,486.027	10518.202	16743.823	11593.146
Kleibergen-Paap F test statistic	259.700	7.552	130.351	448.096	890.455
Kleibergen-Paap LM test statistic	127.859	37.288	162.654	177.566	245.107
Adj.R^2	0.170	0.178	0.177	0.189	0.185
No. of observations	50,176	21,646	25,562	24,932	25,223

Notes: In all blocks, dependent variable is the probability of being NEA (see the list of the covariates in Appendix A). The polynomial functions are allowed to have different parameters to the left and right of the threshold. Robust and clustered standard errors are shown in brackets. For the second and third blocks, first-stage regressions are probit models. Asterisks: *p-value* levels (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$). Tests for weak and underidentification of the instrument F statistics and Wald statistics based on Cragg and Donald (1993) and Kleibergen and Paap (2006).

analysed, and for the age range from 41 to 60 for the male subpopulation. In contrast to the previous plot, the probability of being NEA is higher for men, especially in the age range from 46 to 50.

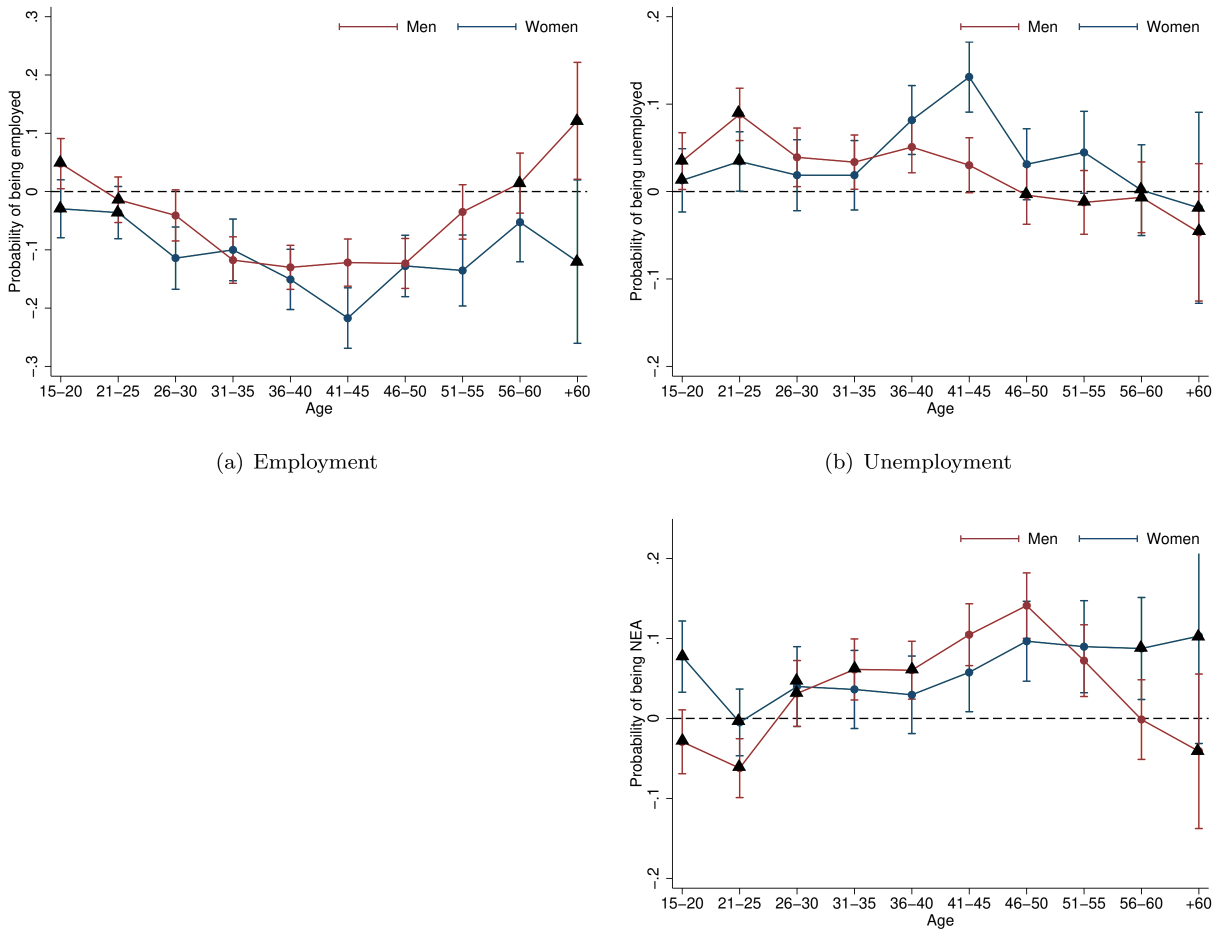
5. Robustness

In this Section, we provide further evidence on the internal validity of the RDD and inspect the external validity of the design.

First, not all households with a child in the eligible age range receive the CSG, since they must also meet an eligibility requirement based on income means test, and this criterion has changed over time. A selection bias may therefore emerge if we do not take into account how participation in the programme varies with changes in the income requirement. The database does not allow us to examine these changes explicitly. In addition, since households may manipulate their income to satisfy the eligibility criterion, the internal validity assumption may be violated. To overcome these shortcomings, following van der Klaauw (2002), a two-step propensity score (PS) procedure was applied (d'Agostino *et al.*, 2016).

Another concern is that, when households have more than one treated child, a self-selection bias may arise as caregivers, or other members, are already familiar to the programme hence their experience increases the probability of assignment to it. To account for self-selection when individuals are members of households receiving more than one grants from the CSG, we introduce a Chamberlainian's control for individual fixed effects (**?**) in the second-stage analysis. When neither the income requirement nor the self-selection bias affect the estimated results, no significant difference is found between the two-step PS and the IV estimates.

Secondly, the external validity of the evaluation requires the outcomes for the treated and non-treated populations away from the cutoff to be constant (d'Agostino *et al.*, 2016). To check whether the external validity assumption holds, we analyse the constancy of the LATE and HLATE for birth cohorts away from the 1994 cutoff by comparing the results obtained through the IV estimator with those through the IDW



(a) Employment

(b) Unemployment

(c) NEA

Figure 4: Marginal effects of CSG on outcome variables, by age: men and women subpopulations

Notes: Black triangle indicates marginal effects not statistically significant (i.e., p-value> 10%).

estimator[9]. Since the IDW provides higher weights for cohorts near the cutoff, if the LATE and HLATE are constant, we do not expect any significant differences between IDW and IV estimates.

The results of these analyses are presented in Table 5. The table is organised horizontally in three blocks and vertically in six columns. The three blocks refer to third-order polynomial specifications of the control function: we first estimate the LATE and then two HLATE estimates considering the gender and OAP interaction variables, respectively. The six columns present the results for each labour market state, distinguishing between the IDW and the PS estimates.

Looking at the table, we find that the RDD results have both strong internal and external validity as, in the majority of cases, the parameters estimated with the IDW and PS methods are contained in the same confidence intervals of the IV estimates. The only divergences concern the PS estimate of the employment's probability (first block, 7%, p-value $< 1\%$), which is lower than the one estimated in Table 1 (), and the PS estimate of the HLATE, when accounting for the impact of the CSG on the probability of being NEA by gender (6.4%). In the latter case, we find that the parameter is significant only at 10% level.

[9]For an application of this approach, see, for example, Pieroni and Salmasi (2015).

Table 4: Robustness checks

	Employed		Unemployed (searching)		NEA	
	IDW	PS	IDW	PS	IDW	PS
Child support grant	-0.078 ***	-0.070 ***	0.068 ***	0.068 ***	0.018	0.017
	(0.012)	(0.017)	(0.010)	(0.012)	(0.012)	(0.016)
Cragg-Donald F statistic	60464.775		63514.708		63514.708	
Kleibergen-Paap F test statistic	13983.139		14079.495		14079.495	
Adj. R^2	0.188	0.189	0.075	0.075	0.170	0.170
No. of observations	47,895	47,895	50,176	50,176	50,176	50,176
			Gender heterogeneity			
CSG	-0.196 ***	-0.192 ***	0.097 ***	0.104 ***	0.064 **	0.064 *
	(0.033)	(0.043)	(0.024)	(0.029)	(0.028)	(0.036)
CSG X Gender	0.070 ***	0.072 ***	-0.018 *	-0.022 *	-0.027 *	-0.028
	(0.019)	(0.023)	(0.010)	(0.014)	(0.016)	(0.020)
Gender (women)	-0.227 ***	-0.222 ***	0.027 ***	0.021 ***	0.179 ***	0.178 ***
	(0.013)	(0.013)	(0.009)	(0.008)	(0.011)	(0.011)
Cragg-Donald F statistic	30434.932		31992.609		31992.609	
Kleibergen-Paap F test statistic	6,936.012		7,006.826		7,006.826	
Kleibergen-Paap LM test statistic	1,731.603		1,765.318		1,765.318	
Adj. R^2	0.189	0.190	0.074	0.075	0.170	0.170
No. of observations	47,895	47,895	50,176	50,176	50,176	50,176
			OAP heterogeneity			
CSG	-0.095 ***	-0.087 ***	0.053 ***	0.054 ***	0.042 ***	0.040 **
	(0.013)	(0.018)	(0.010)	(0.013)	(0.013)	(0.017)
CSG X OAP	0.024 ***	0.022 ***	0.020 ***	0.017 ***	-0.034 ***	-0.029 ***
	(0.009)	(0.008)	(0.007)	(0.005)	(0.010)	(0.008)
OAP	-0.037 ***	-0.033 ***	-0.015 **	-0.010 ***	0.040 ***	0.032 ***
	(0.008)	(0.006)	(0.006)	(0.004)	(0.008)	(0.006)
Cragg-Donald F statistic	19076.170		18257.807		18257.807	
Kleibergen-Paap F test statistic	263.612		259.713		259.713	
Kleibergen-Paap LM test statistic	120.072		127.935		127.935	
Adj. R^2	0.189	0.189	0.075	0.076	0.170	0.171
No. of observations	47,895	47,895	50,176	50,176	50,176	50,176

Notes: See the list of the selected covariates in Appendix. The polynomial functions are allowed to have different parameters to the left and right of the threshold. Robust and clustered standard errors are shown in brackets. For the second and third blocks, first-stage regressions are probit models. Asterisks: *p-value* levels (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$). Tests for weak and underidentification of the instrument F statistics and Wald statistics based on Cragg and Donald (1993) and Kleibergen and Paap (2006).

6. Conclusions

This paper estimates the impact of the South African CSG on the employment status of the adult members of beneficiary households. We use the dataset provided by the NIDS covering 2008, 2010-2011 and 2012 and carry out a fuzzy RDD to estimate the LATE. We also identify how the effect of the CSG varies with the number of treated children in beneficiary households. In addition, we capture two sources of heterogeneity across units in the impact of the CSG on labour market, i.e. gender and household members receiving the OAP social grant.

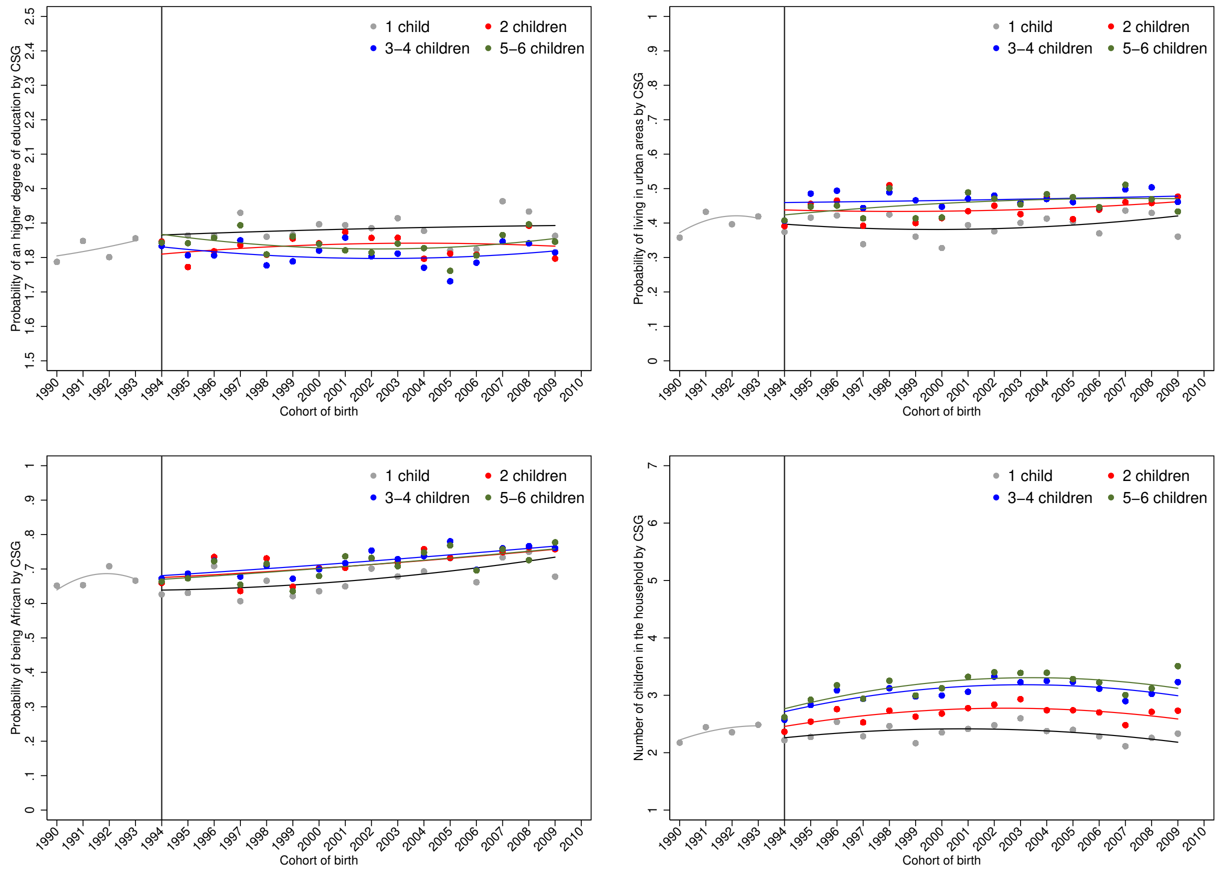
Our evaluation shows that the CSG had a negative effect on the probability of being employed for the adult members of beneficiary households. This negative effect was particularly strong for women, and it worsened when households received benefits for more than one child. Similarly, the negative effect was stronger for members of households receiving both the CSG and the OAP. Overall, these results suggest that the CSG had perverse incentives on the behaviour of the adult members of beneficiary households and caused significant "grant dependence", especially in women, thus increasing gender inequality in the labour market.

Some policy implications are drawn from this analysis. First, establishing a flat transfer of appropriate size, not tailored according to the composition of the beneficiary family, would be useful to avoid distortions in the household decisions, especially of women, related to labour supply. Secondly, the eligibility criteria on the basis of the income means test should esplicitly take into account other social grants received by the household members, in particular the OAP, and a better monitoring over time would be necessary. Lastly, the government should intervene directly by reducing labour market failures and improving welfare provisioning to tackle gender inequality and structural poverty, instead of following the strategy of increasing the CSG coverage.

Appendix A: Descriptive statistics

		Mean	Standard deviation
Employed		0.38	0.49
Unemployed		0.15	0.36
Not economically active		0.32	0.47
Gender			
	women	1.65	0.48
Age		35.99	12.59
Degree of education			
	No schooling	0.11	0.31
	Primary	0.17	0.37
	Secondary	0.66	0.47
	Tertiary	0.07	0.26
Old Age Pension			
		0.27	0.45
Number of children			
	No children	0.02	0.14
	One child	0.12	0.32
	Two children	0.22	0.41
	Three children	0.21	0.41
	Four children	0.16	0.37
	Five to nine children	0.25	0.43
	More than 9 children	0.02	0.13
Number of residents			
	1-4	0.18	0.38
	5-9	0.60	0.49
	10-14	0.19	0.39
	15+	0.04	0.20
Race			
	African	0.80	0.40
	Coloured	0.16	0.36
	Others	0.04	0.20
Geographical location			
	Urban	0.44	0.50

Appendix B: Falsification tests on the balance of selected covariates



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