Does Child Support Grant incentivise childbirth in South Africa?

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Does Child Support Grant incentivise childbirth in South Africa?*

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Abstract

We consider the perverse incentive that can be created for poor households that are benefiting from the South African Child Support Grant (CSG). We acknowledge the fact that the CSG has been successful in improving child outcomes. However, if caregivers see the CSG as a livelihood strategy and respond with multiple births, this will jeopardize the fiscal sustainability of the transfer in the long run. Such incentive will also perpetuate poverty and inequality which will defeat the very purpose the CSG is meant to achieve.

Using the National Income Dynamic Study (NIDS) data, we estimate the relationship between CSG receipt and birth attempts over the last decade using count data models. To control for selection, we use instrumental variable under the Control Function (CF) method. We also check the robustness of our result to alternative assumptions like fixed effects.

Our result is robust over the different identification assumptions and shows that those who benefit from the CSG have had more birth attempts within the last decade when compared to non-beneficiaries.

JEL code: I38, I32, I31, Q56, R23, D61

Keywords: Social transfers; Poverty; Provision and Effects of Welfare Programs

1 Introduction

State welfare transfers are considered to be important instruments of redistribution in an increasingly unequal world. However, these welfare payments can create unintended negative effects which will, ultimately defeat the very purpose that the transfers are meant to achieve. Specifically, the perverse incentives

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generated by the transfers could, not only jeopardize their fiscal sustainability in the long run, but it may also perpetuate poverty and inequality. It is, therefore, of utmost importance that welfare transfers are not just targeted correctly, but that they provide the right incentive. A recognition of this is seen in studies in the United States (US) context that have investigated the impact of the 'Aid to Families with Dependent Children' program on fertility rate and family structures (Acs, 1996; Kaerney, 2004; Groggar & Bronars, 2001; Jagannathan & Cammasso, 2003; Moffitt *et al.,* 2015). These studies investigated the concern that these welfare transfers can become a livelihood strategy, such that women have multiple births, both to increase their incomes and, to prolong their stays on the welfare roll. The response to this concern has resulted in policy proposals such as the 'family cap'. In the United States, the family cap would deny higher welfare payments to women who have another child while on welfare (Acs, 1996). The aim of the family cap legislation, thus, is to reduce childbearing among mothers already receiving welfare.

In South Africa, the Child Support Grant (CSG) is the largest welfare scheme after the Old-age pensions. The share of the CSG in Total Grant Expenditure increased from 31.4% in 2007/08 to 37.2% in 2018/19 (National Treasury, 2019a). In turn, Grant Expenditure as a proportion of Total Expenditure increased from 9.9% in 2010 to 11.4% in 2018. The picture becomes even more worrisome when looking at the CSG as a percentage of Total Tax Revenue where the rate increased from 6.6% in 2010 to 13.7%. While the compounding effect of low economic growth as well as increased child welfare costs cannot be ignored, the increase raises the issues of fiscal sustainability of grants, especially in the context of low economic growth and growing fiscal debt which South Africa has experienced in recent times (National Treasury, 2019b). Currently, the CSG in South Africa has a cap of 6[1] children, which can be argued to leave adequate room for possible exploitation. It is extended to 6 legally adopted or biological children within a household who are aged 18 years and under. Eligibility is based purely on the 'means test' which is a function of the parents' income, which raises the question of whether this grant is being utilised as a household income supplementation strategy.

Although the CSG is seen to be an insignificant amount at R430 (per child), considering that the current food poverty line is R547 (as at April 2018 prices), it is not entirely negligible from the perspective of the 55% of South African households (StatsSA, 2018) living below the poverty line (Budlender & Lund, 2011). Furthermore, the total amount derived through this source can be increased through multiple children within a household.

The impact of CSG has been mostly studied in the South African context from child nutrition and education perspective. Studies show that grant recipients stay in school longer (Case *et al.,* 2005) and that there is beneficial effect on children's nutritional status (Aguero *et al.,* 2009; Oyenubi, 2020), both of which are expected to have positive consequences for the child's long-term life outcomes. Coetzee (2011), however, points out that, although a positive treat-

[1] see https://www.westerncape.gov.za/service/sassa-child-support-grant

ment effect for children's height-for-age and progress through the school system is observed, the estimates are small and indicate that these unconditional grants are used to support overall household consumption, a partial benefit which the children benefit from.

The purpose of this study is not to contest the benefits of the transfer to children, but rather to explore whether it incentivises childbirth, specifically for those who are already benefiting. The focus on childbirth incenticvisation approach to fertility, adopted in this study, deviates from the approach adopted in existing studies which have investigated the relationship between CSG and fertility behaviour, captured as incidences of teenage pregnancy. This has not just direct and immediate fiscal implications, but in the long run, raises questions of poverty traps for larger households (Woolard & Klasen, 2005). In the context of unemployment levels which, currently, are over 50% among youth and above 27% among the total population (StatsSA, 2019), this is a serious concern. Furthermore, since the aim of the CSG is to break the cycle of poverty across generations by providing additional support for the health, education and overall well-being of the child, increased number of children within impoverished households is worrisome as it may lead to a thinner allocation of household resources (Woolard & Klasen, 2005). Therefore, from the fiscal as well as household wellbeing perspective, it is important to study the impact of CSG on higher-order fertility decision of women.

The current study contributes to investigating this conundrum by comparing the fertility behavior of mothers who reported benefiting from the grant in 2008 with those who reported not benefiting in 2008 and 2017[2]. In other words, does benefiting in 2008 or continuous benefit over a decade result in higher birth attempts? Our result is robust to different identification assumption and show that beneficiaries have more birth attempts (on average) than non-beneficiaries over the last decade.

2 Literature Review

Extant studies on the CSG in South Africa, in relation to fertility behaviour, is rather limited and suffers from many technical shortcomings – relying mostly on either qualitative studies or descriptive statistics of fertility rate at an aggregate level (Makiwane *et al.,* 2006). The qualitative studies (Mokoma, 2008; Rabaji, 2016; Dlamini, 2012) have highlighted through interviews, the misuse of CSG evident in women strategically falling pregnant and giving birth in order to access the additional funds. Dlamini (2012) pointed out that teenagers without children were most likely to report that their contemporaries who were teenage mothers chose to have children to receive the CSG, although the teenage mothers themselves did not confirm this. Also, more males than females believed that teenagers take advantage of the CSGs. On similar lines, Edward (2015) highlights the differences in the perception of the use of CSG between recipients

[2] We also compare those who are benefiting in both waves with those who are not benefiting in both waves and our results are similar.

and community members. While community members felt that the CSG was being misused, the grant recipients themselves did not agree. These qualitative studies, however, lack external validity because of their limited sampling and the non-representative nature at the national level.

Depending primarily on descriptive statistics, Makiwane *et al.,* (2006) use aggregated national statistics to conclude that there was no relationship between teenage fertility and the CSG based on three findings: Firstly, while teenage pregnancy rose rapidly during the 1980s, it had stabilized and even started to decline by the time the CSG was introduced in 1998. Secondly, only 20 percent of teens who bore children were beneficiaries of the CSG. Thirdly, observed increases in youth fertility occurred across all social sectors, including amongst young people who would not qualify for the CSG based on the means test criterion. The study, which was based at the aggregate level, can be argued to be highly limited because it did not control for confounding factors in a multivariate framework in arriving at its conclusions.

Udjo (2013) backs up the findings by Makiwane *et al.,* (2006) through micro-level analysis. The study found that black teenagers aged 15-18 years receiving the CSG had significantly lower odds of being pregnant with another child, when compared with black teenagers of the same age who were not receiving the CSG, even after controlling for age, level of education, parental survival, and place of residence. Rosenburg *et al.,* (2015) also found no evidence that the CSG incentivizes pregnancy based on an analysis of the timing of second pregnancy. The study pointed out that CSG is in harmony with South African population policy, and that the receipt of the grant may result in longer spacing between first and second pregnancies. These studies, however, do not look at the impact of child support grants on the mother's higher-order fertility decisions.

From the author's review of existing literature, Kollamparambil (2019) is the only study that looked at the higher-order birth rates with a nationally representative dataset in South Africa. The study utilized the 'Propensity Score' and 'Covariate Matched Average Treatment Effect on the Treated' approaches to ensure that self-selection of grant recipients into the treatment group did not bias the results. Results showed that mothers receiving the CSG had, on average, have more children as compared to those not receiving the grant, for age categories ranging from thirty years and over (note that this implies that the effect was is not significant for younger women including teenagers). The study, however, was based on a severely limiting assumption, in that it assumed that a mother receiving the CSG for her child had received it for all her earlier children. This assumption can bias the estimated impact of CSG on fertility decisions.

In contrast to Kollamparambil (2019), the current study argues that experience may be playing a mediating role in these fertility dynamics and, hence, looks at fertility decisions over a period of ten years. This approach is based on the idea that the incentive to change childbearing behaviour may only occur (i.e. be higher) for women who have gone through the process of applying for the CSG before. This is, perhaps, the reason why Kollamparambil (2019) found a significant effect only for mothers older than thirty years. This argument is plausible as the process of applying for CSG can prove difficult, especially when the parent or guardian does not have the right documentation. Delany *et al.,* (2008) noted that the most common challenge for people applying for the grant is securing the right documentation. To receive the grant the caregiver must supply several documentations to prove that they are the primary caregiver. Furthermore, the caregiver needs to provide proof of immunization and proof of efforts to secure employment or to join a development programme[3]. This perhaps explains why one should expect the incentive to change behaviour to be lower among new mothers, teenagers or more generally mothers who are not already on the CSG roll. However, after this initial difficulty, the dynamics can be different.

3 Method

In the current study, we relax the assumption in Kollamparambil (2019) by looking at the number of birth attempts over the last decade (2008 – 2017) for mothers who are already benefiting from the grant. Our assumption is that if the CSG influences the procreation behaviour of beneficiaries, then we would expect the sub-population that reported benefiting in 2008 to have significantly more birth attempts than the general population. Note that this outcome speaks to higher-order fertility decision because all the women in our "treatment" sample have at least one child in 2008. To capture the birth attempts, we consider the response to the question "how many children have you given birth to in total? (please include all children, even ones who may have passed away shortly after birth)". We add one to this number if the mother reported being currently pregnant. The difference between these figures for wave 1 (2008) and wave 5 (2017) is our outcome variable.

Since this outcome is a count, we consider the Poisson, Control Function (CF) Poisson and Fixed Effects Poisson regression to control for endogeneity[4]. To address the problem of overdispersion, we use the Poisson model that corrects the standard error for dispersion. For the CF Poisson model, we use a variable that jointly captures mother's experience and the possession of a key documentation in applying for the CSG. Specifically, we create this composite variable from two variables – possession of a South African ID, and estimate of the number of grants a mother is receiving in 2008[5]. To get an estimate of the number of grants, the amount a mother reports to be currently receiving from the CSG is divided by R210 (which was the pay-out in 2008)[6]. The implication

[3] Also see https://www.groundup.org.za/article/everything-you-need-know-about-social-grants_820/"

[4] As robustness check we also explore other models like the zero-inflated Poisson model and the negative binomial model.

[5] The instrument is a product of two variables. The first variable -possession of ID is a dummy variable that is equal to 1 if the mother has an ID and zero otherwise. The second variable is an estimate of the amount of CSG grants the mother currently receives.

[6] In the initial draft we use both possession of South African ID and the stated instrument (i.e. experience) as instruments. However, since the ID question is not asked in wave 1

is that this variable is equal to zero if the mother has no ID, or if the mother has an ID but is not a CSG recipient; is equal to 1 if the mother is a recipient of one grant and has an ID; and is greater than 1 if the mother has an ID and receives multiple grants. Note that the size of this instrument corresponds to the intensity of participation.

This (composite) variable, therefore, captures both possible restriction in being on the CSG roll (because ID is an administrative requirement to receive the CSG), and a factor that may influence continuous participation (based on the assumption that those who have already gone through the application process before may find it easier to enrol another child). The variable is therefore relevant because it is correlated with participation (in general). Furthermore, the instrument is uncorrelated with the outcome because neither possession of a South African ID, nor the number of CSG grants being received, should affect fertility behaviour except through participation or continued participation in the CSG.[7] Delany *et al.,* (2008) noted that lack of documentation in the form of the South African Identity document (and birth certificates) is a major stumbling block in terms of accessing the CSG. Furthermore, the results of Kollamparambil (2019) suggest that experience in terms of number of successful applications for the grant may be relevant in predicting continuous treatment. However, we note that this experience should not influence the outcome directly.

3.1 Count data Models

More formally, the outcome is a non-negative count of the number of birth attempts between 2008 and 2017 denoted y, [8]$y = 0, 1, 2...5$. We are interested in how CSG receipt status affects the regression function $E[y|CSG]$, and assume that during a specified exposure period t, y has the probability mass function

$$f\left(y \mid \mu, t\right) = \frac{e^{-\mu t}(\mu t)^y}{y!}, \; y = 0, 1, 2...5$$

of NIDS, and it can be argued that this question has poor response rate in wave 2 we use experience alone.

[7]We note that one option is to use the variables (ID and experience) individually. In results that are not presented here, we found that using experience alone does not change our conclusion, while using ID alone suggest that treatment is not endogenous. Specifically, the auxiliary variable for the Control Function is not significant when only the ID is used as an instrument. The implication of this is that, in this particular model, our treatment variable is exogeneous and the result we have for 'count models without control for endogeneity of treatment', holds. This may be the consequence of sourcing information about possession of ID from Wave 2 since this question was not asked in wave 1. The approach of using ID alone, therefore, assumes that those who have an ID is wave 2 also had IDs in wave 1. Given that there are approximately 2 years between Waves, this may not be true for some respondents. We deal with this by combining the amount reported to be received from the CSG in Wave 1 to mitigate measurement error. In other words, mothers that did not have an ID in Wave 1 would have reported zero for amount received from CSG.

[8]We stop at 4 because this is the highest number of birth attempt observed in the data over the last decade. This is logical because in a period of ten years (accounting for pregnancy period) it is highly unlikely to record a higher count.

Note that since $t = 10years$ for all observations, this parameter is a constant across observations and can be ignored. Parameter μ is the risk of observing a new birth attempt. Note that the Poisson distribution has the property that the mean is equal to the variance – i.e. $E(y) = var(y) = \mu$, and violation of this restriction leads to overdispersion problem. Poisson regression results from the parameterization $\mu = \mu(X)$ where X is a K-dimensional matrix of regressors. The specification can be written as

$$E[y|\mu] = (\hat{\mu}) = e^{X'\beta}$$

If the Poisson model is the correct model, then the maximum likelihood estimator MLE $\hat{\beta}_p$ is consistent and has covariance matrix

$$\hat{V}\left(\hat{\beta}_p\right) = \left(\sum_{i=1}^{N} \hat{\mu_i} x_i x_i\right)^{-1}$$

This formula will be misleading if the assumption of *equidispersion* (i.e. conditional on the covariates the mean is equal to the variance) is incorrect (Culyer, 2014). More generally, there are two main complications that may occur when using the Poisson regression model, both of which are not mutually exclusive. The first one is *overdispersion. Overdispersion* means that the actual data possessed too much variability to be represented by a standard Poisson model (i.e. the variance is greater than the mean). The second complication is when the Poisson regression has a high count of zeros. For example, the inclusion of a group of people who would never display the behaviour may lead to excess zeros (e.g. unobserved personal preferences may be important when it comes to the decision to procreate in the first place).

Overdispersion results from many different sources. In cross-sectional data, there are two main reasons (1) there may be individual differences in responses that are not accounted for by the regression model (i.e. omitted variables[9]) (2) contagion or state dependence (i.e. the count that occurs for an individual may not be independent of the previous occurrence of the event (Coxe *et al.,* 2009). An overdispersed Poisson model will, hence, underestimate the standard error.

The simplest adjustment for *overdispersion* is to consider the overdispersed Poisson model (Gardner *et al.,* 1995; Land *et al.,* 1996; Long, 1997). This model involves the use of the *overdispersion* scaling parameter φ. The model estimated with this correction assumes that the error distribution has mean μ and variance $\mu\varphi$. Therefore, the overdispersed model allows the conditional variances to be larger than their corresponding conditional means, thereby relaxing the assumption of the Poisson model. As a consequence, the Standard

[9] For example, for cultural reasons, procreation behaviour may be different across different races or ethnic groups (Swartz, 2009). Hence, if race or ethnicity is not controlled for, there will be omitted variable problems. Note that the fact that our outcome variable is defined as the number of birth counts within a specified period makes it similar to a difference-in-difference estimator. This means that the model can be thought of as controlling for time invariant factors.

Error of the overdispersed model will be larger than the Standard errors in the standard Poisson model by a factor of $\sqrt{\varphi}$ (Coxe *et al.*, 2009). the main analysis in the current study is based on the overdispersed and the CF version of the Poisson model to control for endogeneity of CSG participation. However, as a robustness check, we consider a number of other models.

There are other models that follow the logic behind the overdispersed Poisson model in accounting for overdispersion. The logic is that if the conditional mean is correctly specified, $\hat{\beta}$ is a consistent estimate of β but the estimator is not efficient (see Culyer (2014, p. 306-307)) when the Variance is larger than the Mean. An example is the Negative Binomial Regression.

The other adjustment we consider is the possibility of Structural Zeros. Count models are typically right-skewed, meaning that there are many low values of the dependent variable. Some outcomes may, however, exhibit more low values than expected from a Poisson model. For example, our sample may include individuals who cannot procreate for biological reasons or choose not to procreate due to personal preferences. The birth count for such individuals will always be Zero. The implication is that observed Zeros can be thought of as coming from two groups in the population: Never takers who produce Structural Zeros and women who produce Zero in the observed interval with some probability[10]. Under the assumption that we have no information that can help identify Structural Zeros, the Zero-inflated Poisson model can be used (Greene, 1994; Hall & Zhengang, 2004; Long, 1997). This model has two parts: in the first part, a Probit model is used to estimate the probability that the outcome for an individual is Zero given observed covariates; while the second part estimates a Poisson model for the part of the data that does not contain Zeros.

We also consider the possibility that there might be selection such that the beneficiaries of the CSG are different from non-beneficiaries in terms of the observed covariate. Under the Conditional Independence Assumption (CIA), we use the entropy balancing (*ebalance*) approach of Hainmueller (2012; 2013)[11] to estimate the Average Treatment Effect on the Treated (ATT) of CSG receipt on procreation behaviour. Under the *ebalance* approach, weights are calculated for each unit so that the weighted treatment and control groups satisfy a prespecified balancing condition. This approach has also been shown to deliver better performance than the Propensity Score Matching (PSM) method in terms of Mean Square Error, and reduced model dependency (Hainmueller, 2012). The balancing weights from the entropy scheme can be combined with any standard estimator that one may wish to use to estimate treatment effect (Hainmueller, 2012, p. 26). We, therefore, use the weights with the overdispersed Poisson

[10] Sometimes the data contains information that can help identify Structural Zeros (e.g. if the data has information on individual preferences when it comes to childbearing or factors that affect an individual's fertility). In this case, one can use the information to trim the sample such that the estimation sample contain respondents who can potentially procreate (Coxe *et al.,* 2009). In the absence of such information, the zero inflated Poison model can be used.

[11] This approach is similar to the Inverse Probability Weighting method.

model to estimate the impact.

Lastly, we consider the Fixed Effect Poisson model, the rational being that there might be time-invariant unobserved factors that influence fertility behaviour.

3.2 Data

We make use of Waves 1 and 5 of the National Income Dynamics Studies (NIDS) dataset. NIDS is the only individual level, nationally representative, panel dataset in South Africa. Each wave is conducted in, approximately, two-year intervals and comprises extensive information on a range of variables relating to the socio-economic and health conditions of South Africans. The five existing NIDS waves cover about ten years between the period 2008-2017. Women between the ages of 15 and 45 years are identified in Wave 1. These same women are then identified in the Wave 5 data. The outcome of interest is the number of birth attempts during the period. In other words, we consider the difference in the total number of children ever given birth to including current pregnancy. To be clear, the Treated group contain Women who claim to benefit from the CSG in Wave 1, irrespective of if they are still on the grant in Wave 5. The Control group consist of women who claim not to be benefiting from CSG in Waves 1 and 5[12]. If indeed the CSG provides an incentive to procreate more often (at least in the last decade), then we will expect the birth attempts to, on average, be higher for women that benefit from the CSG relative to the rest of the population. CGS receipt is modelled as a dummy variable that is equal to one if the respondent indicates that she receives CSG (for at least one of her children in Wave 1), and zero otherwise.

We control for a number of covariates that can explain procreation behaviour. These include number of years of education, age, age at first birth, birth count in Wave 1, number of children who have died in wave 1, years of education, marital status, employment status, self-reported health status, dummies for religious affiliation, race and the income quintile of the respondent's household in 2008 (note that these covariates are sourced from Wave 1 data). The expected influence of these control variables is as follows: number of years of education is expected to decrease the total number of birth attempts (Bittencourt 2018). This is because more educated women are more likely to be employed and these decreases the amount of time they can allocate to childbearing. Furthermore, these women are more likely to be health-conscious and may procreate less because of the inherent risk of pregnancy. Educated women are more likely to be earning an income so they will either not qualify to receive the CSG or

[12] Note that this means the treatment group contains 2 groups, those who are benefiting in waves 1 and 5 and those who were benefiting in wave 1 but have dropped off the CSG roll by wave 5. Table B2 in the appendix shows that about 20% of beneficiaries in wave 1 reported not benefiting from the grant in wave 5.

Furthermore, in wave 1 there are 9,343 women in that adult data. 4,972 of these made it into the balanced sample (i.e. have observation in waves 1 and 5). After restricting the data to those between 15 and 45 years and those who were treated in wave 1 or were untreated in waves 1 and 5, we are left with 2,473 observations.

the amount received from the CSG may not be enough to incentivise them to change their procreation behaviour.

Since fertility has a natural limitation around age 45, one may expect older women that are close to 45 years to give birth to more children (for example consider two women who have a child and who intend to give birth to two children; if one of them is 20 years and the other is 35years old, the 35-year-old may be more likely to procreate within the next decade). As the example suggests, the relationship between age and procreation may depend on the age at first birth as those who give birth early may procreate less within the immediate future. The number of children that died within the last decade is expected to increase the birth attempts. The relationship between marital status and childbearing may be unclear *a priory*, however, married women, and women with partners, may be expected to procreate more than women that are divorced, widowed or have never been married. The effect of employment status is expected to be similar to that of the number of years of education. Healthier women are expected to procreate more and African women are also expected to procreate more (available evidence suggest that while fertility rate has decreased in South Africa, African women still have a higher fertility rate than other race groups (Lehohla, 2010; Swartz, 2009)).

The summary statistics are shown in Table 1. Without adjusting for control variables, the birth rate over the last decade is higher for beneficiaries but so is the death rate of children in wave1.

Figure 1 provides a histogram of the number of children that were born to mothers during the ten-year period of the study with a clear concentration at zero. This motivates the use of the overdispersed Poisson model described in the method section.

4 Results

The beta estimate in a Poisson regression represents the difference between the Log of Expected Counts. In our case and for our variable of interest, the beta estimate represents the difference between the Log of Expected Birth counts when the dummy variable that indicates receipt of CSG changes from zero to one, *i.e.*

$$\beta = \log(CSG_1) - \log(CSG_0)$$

To properly interpret the result, we consider the marginal effect (*i.e.* how much the birth count changes when CSG status changes from 0 to 1).

Table 2 presents results the overdispersed Poisson model. The result shows that the difference between the Log of Expected Birth Count between beneficiaries and non-beneficiaries of CSG is 0.49. The marginal effect shows that this translates to beneficiaries having 0.28 more births attempts compared to non-beneficiaries. These estimates are significant at 1%.

The other significant results are as follows, a unit change in the number children in 2008 increases the birth attempts by 0.05; women that are a year older in 2008 have 0.06 fewer birth attempts; procreation is 0.03 higher among women who are a year older for their first birth; and married women and women who are living with a partner have more birth attempts than women who are never married by 0.13 in both cases. Birth attempts among Christian women is 0.12 less than those in 'other' religious groups and birth attempts is higher by 0.47 and 0.43 for black and coloured women (respectively) relative to white women. The other results are not significant but have reasonable signs. For example, Table 2 also shows that a unit change in years of education is associated with lower birth rate. The results in this table assumes that CSG receipt is exogeneous, so, to control for possible endogeneity of CSG receipt we use the control function method and use the variable described earlier as our instrument.

Recall that this variable is a product of a dummy variable that is equal to 1 if the respondent has the South African Identity card, and an estimate of the number of CSG grants the respondent was receiving in 2008. This variable is correlated with initial participation (*i.e.* getting on the CSG role for the first time) and continued participation (ease of applying for a new grant). Furthermore, we assume that possession of ID and the current number of CSG being received should not affect procreation except through participation or continued participation. Using an instrument that captures both initial participation and possibility of future participation is important in this case. Recall that, as noted in footnote 12, the treatment group can be split into 2: those who continuously receive the CSG throughout the period of interest; and those who received it in 2008 but dropped out before 2017. To capture this "experience", we divide the total grant money being received by each mother by the value of the grant/child as at 2008 – this gives an estimate of the total number of successful applications per mother. The result of this analysis is presented in Table 3.

First, note that the Control Function approach assumes a certain structural relationship between the Endogenous Regressors and the Exogenous Regressors, and use functions of the first-stage parameter estimates to control for the endogeneity in the second stage. Specifically, the approach regresses the CSG indicator on the instruments and the other covariates. The residual from this regression is then included as an auxiliary variable in the second stage to control for endogeneity of the CSG receipt. The auxiliary parameter is -0.464, significant at 10%, which confirms that CSG receipt is endogenous in the model.

Furthermore, the instrument explains significant variation in participation (0.23, significant at 1% (see column 2 in table 3)), showing that the instruments are relevant[13]. Other significant results in the first stage show that women with more children (in Wave 1), younger, older at first birth, married, living with a partner, and coloured or African, are more likely to be beneficiaries.

Our main result shows that the difference between the log of expected birth count between beneficiaries and non-beneficiaries of CSG is 1.04. In terms of the marginal effect, this means birth rate among beneficiaries is higher by 0.85.

[13] In 2008, Regulation 11(1) was introduced which allowed applicants who lack the prescribed documents to use alternative documents, including an affidavit and a range of supporting documents proving identity to support their CSG applications (e.g. clinic cards, affidavits from respected community members, and recent school report cards (SASSA & UNICEF, 2013).

These estimates are significant at 1%. In other words, the result in Table 2 is robust to unobserved factors under the instruments used in this study[14].

The result for the CF Poisson model, therefore, agrees with the result under the overdispersed Poisson model, the only difference being that the CF estimate is larger. CSG beneficiaries have more birth attempts within the last decade when compared with non-beneficiaries.

Our last analysis in this section restricts the sample to those who are from households with household income per capita below the March 2009 upper-bound poverty line (*i.e.* R577 per person)[15]. The logic here is that beneficiaries of the CSG are more likely to come from poor households (given the requirement needed to qualify for CSG).

The results so far may, therefore, be the difference between rich and poor households. Table 4 shows the results when the sample is restricted to those below the March 2009 poverty line. The result shows that number of birth attempts is still higher for beneficiaries when the poverty line is taken into account[16]. These results suggest that CSG beneficiaries are more likely to procreate (when compared with the general population or those who are of similar income level) within the last decade holding other factors constant.

4.1 Robustness checks[17]

In this section, we check if these results are robust to a number of assumptions about the Poisson model.

4.1.1 Overdispersed Negative Binomial Model

Another way to deal with the overdispersed Poisson model is to use the Negative Binomial or/and the zero-inflated Poisson model. The former allows the variance of the outcome to be greater than the mean, while the latter splits the sample into two groups because of Structural Zeros. Table A5 (see the Appendix) presents the results from the Negative Binomial Model[18].

The result in Table A5 agrees with the previous results – the Log of Expected Birth Count is higher for beneficiaries by 0.51 (Marginal effect 0.29 significant at 1%). Next, we consider the Zero-inflated Poisson model. The result is presented in Table A6. Recall that the result for the Zero-inflated model is in two parts. The first part (column 2 in Table A6) shows the Probit model that estimates the probability of observing a Zero-count given the observed covariates. The

[14] Note that when we use the GMM approach instead of control function, our substantive result did not change.

[15] See table 2 on page 8 of this report http://beta2.statssa.gov.za/publications/Report-03-10-06/Report-03-10-06March2014.pdf

[16] We note that this is not surprising since education, race, employment, and income are correlated in the South African context. Since these other factors are controlled for in the previous results it is not surprising that household income per capita does not affect the results.

[17] All tables for the robustness checks are in Appendix 1.

[18] Note that, similar to the Poisson model, we also control for the effect of *overdispersion* in the Standard Error of the model estimates.

result shows that those who benefit from the CSG are less likely to record Zero birth attempt (-0.49, significant at 1%) during the last decade. The second part of the model (column 1 in Table A6) shows that log of expected birth count among beneficiaries is higher by 0.35(significant at 1%)[19].

4.1.2 Poisson Model with Entropy balance

The next model controls for selection under the Conditional Independence Assumption (CIA) by balancing the distribution of covariates. By this, we mean beneficiaries may have different characteristics to non-beneficiaries across the different covariates (not just in terms of household income as done in the previous section). What we can infer from the overdispersed Poisson model is that benefiting from the CSG is correlated with more birth attempts during the last decade. We can, however, make a stronger statement i.e. CSG impacts the procreation behaviour of beneficiaries (relative to the counterfactual). However, this stronger statement is only valid under the CIA assumption. Another way to think of this is that we are comparing beneficiaries with non-beneficiaries who may qualify for the grant (given their covariates) but are not benefiting from the grant for some other reason (e.g. lack of documentation).

To achieve this, we use the Entropy Balance approach to balance the Mean, Variance and the Skewness of the Covariates (See Appendix Table B1 for the balance statistics). The balancing weights are then used with the over-dispersed Poisson model. The results are presented in Table A7.

The result is consistent with previous results – birth rate is higher for beneficiaries (a marginal effect of 0.24, significant at 1%).

4.1.3 Poisson Model with NIDS Stratified Weights

Table A8 presents results from the Poisson model where we use the Post-stratified weights supplied by NIDS. We use the Jack-knife replication method to calculate the Standard Error that takes the complex survey design into consideration for this analysis. The result remains significant with Expected Log of Birth count being 0.48 in favour of beneficiaries.

4.1.4 Fixed Effect Poisson Model

Lastly, we consider the Fixed Effects Poisson model under the assumption that unobserved individual Fixed Effects may bias the result, the result is shown in Table A9. Even though the point estimate reduced to 0.11, the estimate remains significant at 1%. Therefore, across the different models, and based on different plausible assumptions, the result remains robust.

In light of these results, the sustainability argument alluded to in the introductory section is important in making sure that this very important social assistance programme is sustainable.

[19] Marginal effect of the zero-inflated model is 0.22 significant at 1%

4.2 Comparing our result with Rosenburg et al (2015)

We compare our result with Rosenburg et al (2015) because this study, like ours, controls for confounding factors in a multivariate framework in arriving at its conclusions. Furthermore, this study (Rosenburg *et al.,* 2015) investigates the relationship between receipt of CSG and procreation behaviour for all women of productive age, not just teenage fertility. There are a number of reasons why our result presents an opposing evidence to the one presented in Rosenburg *et al.,* (2015).

First, the analysis in Rosenburg *et al.,* (2015) is based on timing of second birth while ours consider procreation attempts over a decade. The impact of the programme in terms of timing of second birth might be very different from the way the programme influences the number of birth attempts over a decade because the samples are very different. The treated mothers in Rosenburg *et al.* (2015) will contain benefiting mother with only one child while our sample will contain all benefiting mothers irrespective of the number of children they have. Our results show that number of children in Wave 1 is positively correlated with birth attempts over the last decade (see Tables 3 to A5). Furthermore, in results not presented here, when we restrict the analysis to mothers that only had one child (or were currently pregnant) in Wave 1, the result remain positive and significant (Marginal effect of 0.35, significant at 1%). Second, Rosenburg *et al.* (2015)'s study is based on women who live in Bushbuckridge district in rural Mpumalanga province (*i.e.* the interpretation of their result is valid in a particular rural area only). Our data is based a Nationally representative dataset and our result remains valid even when the NIDS post-stratified weights are used. South Africa is a heterogeneous society in many respects, including social economic status, race and geography.[20] These factors can have varying impact on procreation behavior.

The third and, perhaps, most important factor is the timing of both studies. Rosenburg *et al.* (2015) considered the timing of second birth for women who had their first child between 1998 and 2008, while our study looks at procreation behavior between 2008 and 2017. This is important in light of the plausible explanations given by Rosenburg *et al.* (2015) as to why they found that CSG does not incentivize childbirth. The authors noted that the amount of money received may not be large enough to incentivize dramatic changes in fertility behavior. As noted in the introduction, this may not be the case for about 55% of South African households living below the poverty line (StatsSA, 2018). Furthermore, they argue that an alternative explanation may be that the income effect may lower pregnancy rate if the extra income facilitate access to health services (including family planning resources), improves jobs prospects, or increase female economic independence. However, this argument relies on the grant money holding its value (in comparison to inflation) over time. For many years, grant increases have barely kept up with inflation. Some researchers[21]

[20] For example, the geographical there are vast differences, there are a lot of urban informal areas where there is high poverty and low service delivery.

[21] https://theconversation.com/south-africa-has-raised-social-grants-why-this-shouldnt-be-

noted recently that, adjusted for inflation, the CSG has either declined or stagnated in value (the most recent increase because of COVID 19 is perhaps a notable exception). This raises the possibility that the CSG may not have the same 'income effect' it had in previous years.

These reasons suggests the results are different, either, because the sample we use and the one used by Rosenburg *et al.* (2015) are different in relevant ways or, the reason why CSG may not have resulted in dramatic changes in procreation behavior may have weakened over time.

Evidence from the USA suggests that it is useful to have a policy that, at least, mitigates unintended perverse incentive. Currently the cap in South Africa stands at 6 children, and our study suggests that this cap may not be effective in preventing possible changes in procreation behaviour. Finally, the evidence in this study suggests that there is a significant correlation between procreation behaviour and receipt of the CSG in a Nationally representative dataset.

Note that even if it is the case that there is some other unobserved factor that explains the procreation behaviour observed among beneficiaries, this is still problematic. This is because it means that those who need to rely on the fiscus to cater for children are procreating more than those who do not need to rely on the fiscus. Although this will mean that the procreation behaviour observed cannot be attributed to the CSG (except the factor is correlated with CSG receipt). This kind of trend is clearly not sustainable. It also has implication for poverty traps for larger households *(Woolard & Klasen, 2005).*

5 Conclusion

The current study analysed the childbirth incentive of the Child Support Grant (CSG) in South Africa by estimating the average number of children born by mothers already receiving the grant and those not receiving it (over the last decade). Even after controlling for a host of confounding factors such as education, age, age at first birth, the number of children at the beginning of the period, health status, employment status, race, and household income, the results indicate that mothers who were receiving CSG in 2008 procreated more, over the last 10 years, when compared to those not receiving the grant. In terms of the number of children, the estimate under the Control Function approach shows that mothers who were receiving the grant in 2008 on average have 0.8 more birth attempts over the last decade compared to the rest of the population. These results point to the existence of an unintended childbirth incentive for the CSG. The literature in the US suggests that this effect is real. Consequently, a policy called family cap was introduced in the US to mitigate the unintended incentive. The way this cap was implemented in US is considerably stricter than what currently obtains in South Africa. The US family cap denies higher welfare payments to women who have another child while on welfare (Acs 1996). This effectively means the family cap is one. While this may be argued to be

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too strict, it does suggest that the family cap of 6 is on the other side of the spectrum. It might be advisable for a 'stricter' policy to be given consideration in South Africa to ensure fiscal sustainability. This is because increased procreation as a result of CSG receipt has implications, not only on the fiscus but also, on long-run poverty, unemployment and inequality.

The findings of the study point to the need to analyse more carefully the unintended impact of the CSG in South Africa, and the self-defeating outcomes that may have been incentivized through it. The policy suggestion would be to structure welfare grants in a way that incentivize behaviour that will align with the developmental goals of the nation. An unconditional, but targeted basic income grant, for example, is likely to have much lesser perverse incentives (Standing & Samson, 2003). A basic income grant provided to a young woman who qualifies through the means test is more likely to result in its productive utilization either for job search, as seed capital for entrepreneurship or childcare, if she chooses. This is more likely to have income effect in the direction suggested by Rosenburg *et al.* (2015), that is, affect health and employment more than when there is a child to take care of. However, this is not to say that direct assistance tied to the child is to be entirely withdrawn. State assistance in kind – through medical assistance, basic childcare products, quality education *etc.*, would provide benefits to the child which cannot be easily diverted for household purposes and, therefore, is less likely to influence childbirth decision.

Reducing the fertility rate is important to address the triple challenge of poverty, unemployment and inequality in South Africa. Given that CSG seems to have the opposite effect, other forms of providing State support to the disadvantaged needs to be developed. State support should be such that it does not have within it, inbuilt perverse incentives. An oftentimes mooted argument is that the South Africa fiscus does not have the capacity to extend the basic income grant for even the most vulnerable. However, this needs to be re-analyzed keeping in mind that it would prove more sustainable in the long ,run rather than providing grants tied to the number of children, which will increase the proportion of grant dependent population at a geometric rate. For example, the government has chosen the route of a Universal Basic Income to alleviate the strain of the on-going COVID-19 pandemic. In a normal non-pandemic environment, this income can generate positive outcomes in terms of health and employment.

The takeaway from the findings of this study is, therefore, not the lack of need for social grants, but rather, an emphasis on the need to provide Social Security without necessitating conditions that would lead to perverse effects. Basic minimum income for women, with or without children, might, in the long run, be more cost effective and fiscally sustainable, rather than linking such transfers to the number of children.

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Table 1: Summary Statistic

	All		Treated		Control	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
Children Count over the Last Decade	0.57	0.8	0.69	0.86	0.31	0.59
Child grant receipt	0.69	0.46	1	0	0	0
Birth Count in Wave 1	2.56	1.63	2.69	1.73	2.28	1.34
No of Dead Children	0.18	0.47	0.18	0.49	0.16	0.42
Age (years)	32.44	7.69	31.26	7.42	35.03	7.64
Age at First Birth (Years)	20.54	3.75	20.27	3.41	21.13	4.34
Years of education	8.94	3.41	8.67	3.38	9.54	3.4
Marital Status						
Married	0.28	0.45	0.22	0.41	0.41	0.49
Living with partner	0.13	0.33	0.14	0.34	0.11	0.31
Widow/widower	0.03	0.18	0.03	0.17	0.04	0.19
Divorced/separated	0.02	0.15	0.02	0.13	0.04	0.2
Never married	0.54	0.5	0.6	0.49	0.4	0.49
Employment Status						
Employed	0.42	0.49	0.35	0.48	0.57	0.5
Unemployed strict	0.2	0.4	0.23	0.42	0.14	0.35
Unemployed discouraged	0.12	0.33	0.15	0.35	0.06	0.25
Health Status						
excellent	0.31	0.46	0.3	0.46	0.32	0.47
Very good	0.28	0.45	0.28	0.45	0.27	0.44
Good	0.26	0.44	0.26	0.44	0.27	0.44
Fair	0.1	0.3	0.11	0.31	0.09	0.29
poor	0.05	0.22	0.05	0.22	0.05	0.22
Religion						
Christian	0.88	0.32	0.87	0.34	0.91	0.28
Traditional religion	0.04	0.18	0.04	0.2	0.02	0.14
Muslim	0	0.06	0	0.02	0.01	0.09
No religion	0.07	0.25	0.08	0.27	0.04	0.19
Race						
African	0.83	0.38	0.88	0.32	0.72	0.45
Coloured	0.14	0.34	0.11	0.32	0.19	0.39
Asian	0.01	0.11	0	0.05	0.03	0.17
White	0	0	0	0	0	0
Household per capita:						
Quintile 1	0.2	0.4	0.22	0.41	0.17	0.37
Quintile 2	0.2	0.4	0.23	0.42	0.12	0.32
Quintile 3	0.19	0.4	0.22	0.41	0.15	0.36
Quintile 4	0.22	0.42	0.24	0.43	0.2	0.4
Quintile 5	0.18	0.38	0.09	0.29	0.37	0.48
Household Type						
Traditional	0.45	0.5	0.52	0.5	0.3	0.46
Urban	0.47	0.5	0.4	0.49	0.63	0.48
Farms	0.08	0.27	0.08	0.27	0.07	0.26
		2472		**1696**		**776**

Table 2:Overdispersed Poisson Model

VARIABLES	(1) Poisson Model	(2) Marginal Effects
Child grant recipient	0.493***	0.282***
	(0.0711)	(0.0413)
Birth count in wave 1	0.0849***	0.0486***
	(0.0300)	(0.0172)
No of dead Children	-0.0573	-0.0328
	(0.0719)	(0.0412)
Age (years)	-0.111***	-0.0636***
	(0.00625)	(0.00391)
Age at first birth (years)	0.0566***	0.0324***
	(0.00914)	(0.00530)
Years of education	-0.00521	-0.00298
	(0.0101)	(0.00577)
Married [x]	0.221***	0.127***
	(0.0751)	(0.0431)
Living with a partner	0.223***	0.128***
	(0.0768)	(0.0441)
Widow/Widower	-0.183	-0.105
	(0.257)	(0.147)
Unemployed Strict [y]	0.0327	0.0187
	(0.0649)	(0.0372)
Employed	-0.0228	-0.0131
	(0.0628)	(0.0360)
Excellent health [z]	0.213	0.122
	(0.155)	(0.0886)
Very good health	0.152	0.0868
	(0.156)	(0.0895)
Good health	0.249	0.142
	(0.156)	(0.0891)
Fair health	0.239	0.137
	(0.171)	(0.0982)
Religion (Christian)[R]	-0.202**	-0.116**
	(0.0822)	(0.0472)
Religion (Traditional)	-0.142	-0.0813
	(0.146)	(0.0837)
Religion (Muslim)	0.0244	0.0140
	(0.481)	(0.276)
African [C]	0.819**	0.469**
	(0.364)	(0.209)
Coloured	0.745**	0.427**
	(0.367)	(0.211)
Asian	0.108	0.0616
	(0.521)	(0.299)
Income quintile 2[F]	-0.0687	-0.0392
	(0.0772)	(0.0441)
Income quintile 3	-0.0303	-0.0176
	(0.0787)	(0.0458)
Income quintile 4	-0.0151	-0.00887
	(0.0762)	(0.0447)
Income quintile 5	-0.0464	-0.0268
	(0.0924)	(0.0530)
Traditional (Geographic Area) [D]	-0.153	-0.0877
	(0.0964)	(0.0552)
Urban	-0.0845	-0.0484
	(0.0962)	(0.0551)
Constant	0.316	
	(0.453)	
Observations	2,472	2,472

[[x] Never married is the base category; [y] Unemployed Discouraged is the base category; [z] Poor health is the base category [C] White is the base category [D] Farms is the base category [F] Income quintile 1 is the base category [R] Other religious groups is the base category.]
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1(Standard errors scaled using square root of Pearson chi-squared-based dispersion.)

Table 3: CF Poisson Results

VARIABLES	(1) 2nd Stage	(2) First stage	(4) Marginal Effects
Child grant recipient	1.040***		0.853***
	(0.239)		(0.208)
Birth count in wave 1	0.163**	0.0113	0.138**
	(0.0655)	(0.00875)	(0.0553)
No of dead Children	0.00485	-0.0135	-0.00114
	(0.140)	(0.0199)	(0.114)
Age (years)	-0.186***	-0.0137***	-0.158***
	(0.0148)	(0.00149)	(0.0187)
Age at first birth (years)	0.0797***	0.00592***	0.0676***
	(0.0177)	(0.00224)	(0.0154)
Years of education	0.0224	-0.00576	0.0162
	(0.0233)	(0.00350)	(0.0190)
Married [x]	0.307**	-0.0858***	0.219**
	(0.137)	(0.0196)	(0.109)
Living with a partner	0.364**	-0.000969	0.298**
	(0.154)	(0.0246)	(0.128)
Widow/Widower	0.196	-0.00665	0.158
	(0.370)	(0.0509)	(0.301)
Unemployed Strict [y]	-0.0691	0.0357*	-0.0431
	(0.118)	(0.0197)	(0.0961)
Employed	-0.0748	-0.0149	-0.0670
	(0.117)	(0.0180)	(0.0957)
Excellent health [z]	0.0564	-0.0327	0.0338
	(0.325)	(0.0386)	(0.266)
Very good health	-0.181	-0.0150	-0.154
	(0.321)	(0.0387)	(0.264)
Good health	0.0909	-0.0173	0.0679
	(0.324)	(0.0387)	(0.266)
Fair health	-0.329	-0.0181	-0.276
	(0.337)	(0.0431)	(0.278)
Religion (Christian)[R]	-0.448**	-0.0228	-0.376**
	(0.174)	(0.0293)	(0.150)
Religion (Traditional)	-0.514*	0.0416	-0.406*
	(0.282)	(0.0473)	(0.235)
Religion (Muslim)	-0.441	-0.146	-0.417
	(0.744)	(0.102)	(0.604)
African[C]	2.171***	0.188***	1.851***
	(0.521)	(0.0353)	(0.450)
Coloured	2.079***	0.162***	1.767***
	(0.527)	(0.0379)	(0.453)
Asian	0.737	0.0186	0.611
	(0.722)	(0.0572)	(0.589)
Income quintile 2[F]	-0.244	0.0545**	-0.177
	(0.149)	(0.0235)	(0.123)
Income quintile 3	-0.140	0.0245	-0.108
	(0.158)	(0.0244)	(0.135)
Income quintile 4	-0.105	-0.00539	-0.0920
	(0.157)	(0.0241)	(0.135)
Income quintile 5	0.0943	-0.164***	0.0165
	(0.190)	(0.0275)	(0.167)
Traditional (Geographic Area) [D]	-0.117	0.00676	-0.0934
	(0.207)	(0.0327)	(0.170)
Urban	0.170	-0.0217	0.131
	(0.204)	(0.0320)	(0.167)

Instrument		0.232***	
		(0.0104)	
Auxiliary Variable	-0.464*		
	(0.263)		
Constant	0.290	0.729***	
	(0.763)	(0.0902)	
Observations	2,156	2,156	2,156

[x Never married is the base category; y Unemployed Discouraged is the base category; z Poor health is the base category. C White is the base category; D Farms is the base category F Income quintile 1 is the base category; R Other religious groups is the base category.]

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

Table 4: Overdispersed Poisson Model for household below the upper poverty line

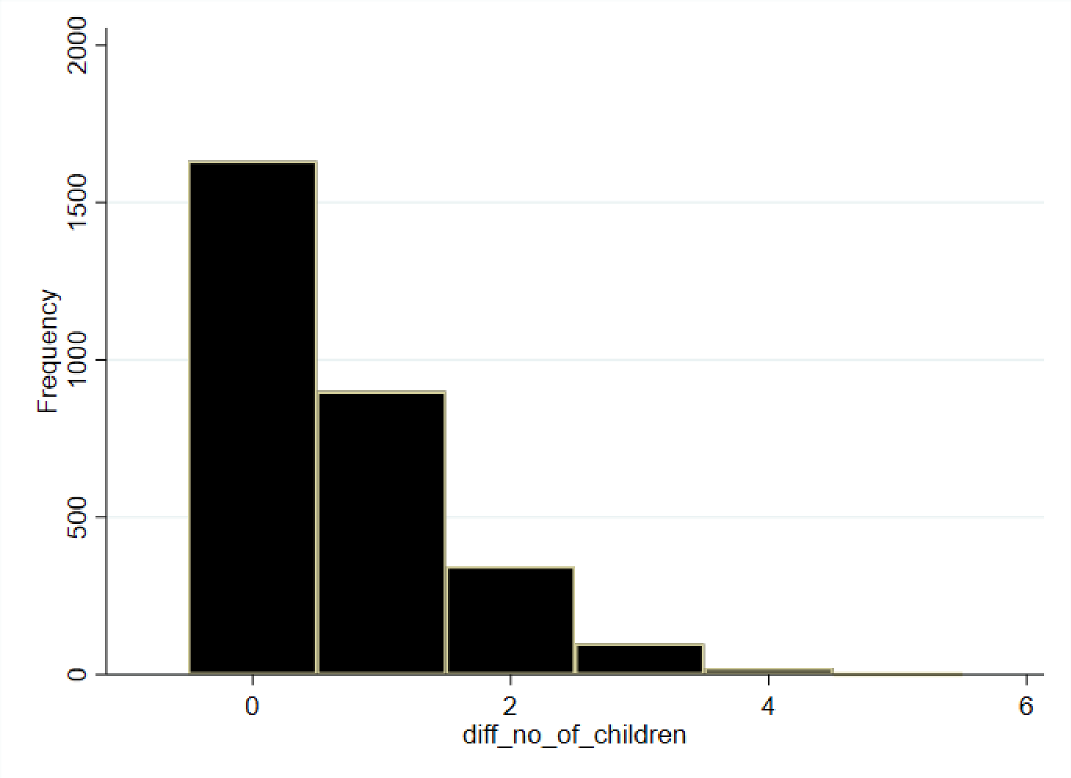
	(1)	(2)
VARIABLES	**Poisson Model Poverty line**	**Marginal Effects**
Child grant recipient	0.472***	0.296***
	(0.100)	(0.0634)
Birth count in wave 1	0.107***	0.0669***
	(0.0354)	(0.0223)
No of dead Children	-0.146*	-0.0917*
	(0.0885)	(0.0555)
Age (years)	-0.108***	-0.0680***
	(0.00791)	(0.00537)
Age at first birth (years)	0.0629***	0.0394***
	(0.0119)	(0.00755)
Years of education	-0.0151	-0.00945
	(0.0115)	(0.00720)
Married[*]	0.159	0.0998
	(0.0973)	(0.0611)
Living with a partner	0.110	0.0690
	(0.104)	(0.0653)
Widow/Widower	-0.351	-0.220
	(0.325)	(0.204)
Unemployed Strict[**]	0.0973	0.0610
	(0.0744)	(0.0467)
Employed	-0.187**	-0.117**
	(0.0853)	(0.0536)
Excellent health[***]	0.109	0.0685
	(0.185)	(0.116)
Very good health	0.0494	0.0309
	(0.186)	(0.117)
Good health	0.138	0.0866
	(0.186)	(0.116)
Fair health	0.125	0.0785
	(0.206)	(0.129)
Religion (Christian)[R]	-0.173*	-0.108*
	(0.0933)	(0.0586)
Religion (Traditional)	-0.159	-0.0998
	(0.176)	(0.110)
Religion (Muslim)	-11.38	-7.131
	(638.7)	(400.2)
African [C]	12.04	7.543
	(638.7)	(400.2)
Coloured	11.91	7.464
	(638.7)	(400.2)
Asian	10.78	6.755
	(638.7)	(400.2)
Income quintile 2[F]	-0.0427	-0.0267
	(0.0812)	(0.0508)
Income quintile 3	-0.0353	-0.0221
	(0.0880)	(0.0551)
Income quintile 4	-0.0158	-0.0100
	(0.0940)	(0.0595)
Income quintile 5	0.117	0.0796
	(0.193)	(0.137)
Traditional (Geographic Area) [D]	-0.205*	-0.129*
	(0.119)	(0.0748)
Urban	-0.128	-0.0803
	(0.123)	(0.0769)
Constant	-10.87	
	(638.7)	
Observations	1,537	1,537

[[x] Never married is the base category; [y] Unemployed Discouraged is the base category; [z] Poor health is the base category; [C] White is the base category; [D] Farms is the base category [F] Income quintile 1 is the base category; [R] Other religious groups is the base category].

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

(Standard errors scaled using square root of Pearson chi-squared-based dispersion.)

Figure 1: Histogram of Birth Count within the last decade(Authors Calculation)



Appendix A

Table A5: Overdispersed Negative Binomial Model

VARIABLES	(1) Negative Binomial Model	(2) Marginal Effects
Child grant recipient	0.506***	0.298***
	(0.0756)	(0.0459)
Birth count in wave 1	0.104***	0.0613***
	(0.0305)	(0.0181)
No of dead Children	-0.0470	-0.0277
	(0.0736)	(0.0434)
Age (years)	-0.123***	-0.0727***
	(0.00658)	(0.00477)
Age at first birth (years)	0.0585***	0.0345***
	(0.00962)	(0.00579)
Years of education	-0.00110	-0.000651
	(0.0108)	(0.00636)
Married [x]	0.215***	0.127***
	(0.0790)	(0.0468)
Living with a partner	0.243***	0.143***
	(0.0863)	(0.0512)
Widow/Widower	-0.119	-0.0702
	(0.238)	(0.140)
Unemployed Strict [y]	0.0155	0.00911
	(0.0735)	(0.0433)
Employed	-0.0335	-0.0198
	(0.0688)	(0.0405)
Excellent health [z]	0.225	0.133
	(0.159)	(0.0936)
Very good health	0.150	0.0884
	(0.160)	(0.0942)
Good health	0.265*	0.156*
	(0.159)	(0.0942)
Fair health	0.206	0.121
	(0.176)	(0.104)
Religion (Christian)[R]	-0.246**	-0.145**
	(0.0962)	(0.0570)
Religion (Traditional)	-0.225	-0.133
	(0.167)	(0.0987)
Religion (Muslim)	-0.110	-0.0648
	(0.513)	(0.302)
African [C]	0.905***	0.533***
	(0.335)	(0.198)
Coloured	0.831**	0.489**
	(0.339)	(0.201)
Asian	0.149	0.0878
	(0.491)	(0.289)
Income quintile 2[F]	-0.0495	-0.0291
	(0.0866)	(0.0509)
Income quintile 3	-0.0216	-0.0129
	(0.0881)	(0.0525)
Income quintile 4	-0.00722	-0.00433
	(0.0859)	(0.0516)
Income quintile 5	-0.0342	-0.0202
	(0.103)	(0.0607)

Traditional (Geographic Area) [D]	-0.130	-0.0764
	(0.110)	(0.0648)
Urban	-0.0327	-0.0193
	(0.109)	(0.0644)
Constant	**0.461**	
	(0.448)	
Observations	**2,472**	**2,472**

[[x] Never married is the base category; [y] Unemployed Discouraged is the base category; [z] Poor health is the base category; [C] White is the base category; [D] Farms is the base category; [F] Income quintile 1 is the base category; [R] Other religious groups is the base category].
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
(Standard errors scaled using square root of Pearson chi-squared-based dispersion.)

Table A6: Zero-inflated Poisson Model

VARIABLES	(1) **Zero-inflated Model**	(2) **Zero-inflated Model**
Child grant recipient	0.345***	-0.488*
	(0.0848)	(0.291)
Birth count in wave 1	0.00542	-0.242**
	(0.0393)	(0.0973)
No of dead Children	-0.0688	-0.190
	(0.0886)	(0.278)
Age (years)	-0.0570***	0.349***
	(0.00964)	(0.0455)
Age at first birth (years)	0.0308**	-0.0333
	(0.0124)	(0.0367)
Years of education	-0.0120	0.00616
	(0.0121)	(0.0351)
Married [x]	0.208**	0.121
	(0.0909)	(0.290)
Living with a partner	0.123	-0.388
	(0.0885)	(0.386)
Widow/Widower	-0.204	-0.550
	(0.331)	(0.590)
Unemployed Strict [y]	-0.00250	-0.117
	(0.0733)	(0.373)
Employed	0.0159	0.645**
	(0.0731)	(0.305)
Excellent health [z]	0.230	-0.293
	(0.210)	(0.718)
Very good health	0.209	0.311
	(0.211)	(0.696)
Good health	0.243	-0.409
	(0.211)	(0.685)
Fair health	0.355	0.645
	(0.228)	(0.722)
Religion (Christian) [R]	-0.141	1.072
	(0.0936)	(0.674)
Religion (Traditional)	0.108	2.497***
	(0.170)	(0.913)
Religion (Muslim)	0.132	2.904*
	(0.575)	(1.510)
African [C]	-0.162	-2.584***
	(0.441)	(0.776)
Coloured	-0.226	-2.446***
	(0.446)	(0.792)
Asian	-0.391	-0.803
	(0.633)	(0.997)

Income quintile 2[F]	-0.121	-0.451
	(0.0884)	(0.345)
Income quintile 3	-0.0850	-0.312
	(0.0916)	(0.368)
Income quintile 4	-0.107	-0.713*
	(0.0875)	(0.374)
Income quintile 5	-0.111	-0.667
	(0.106)	(0.422)
Traditional (Geographic Area) [D]	-0.187*	-0.274
	(0.112)	(0.487)
Urban	-0.165	-0.564
	(0.112)	(0.466)
Constant	**0.850**	**-9.466*** **
	(0.553)	(2.071)
Observations	**2,472**	**2,472**

[[x] Never married is the base category; [y] Unemployed Discouraged is the base category; [z] Poor health is the base category [C] White is the base category; [D] Farms is the base category; [F] Income quintile 1 is the base category; [R] Other religious groups is the base category].
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
(Standard errors scaled using square root of Pearson chi-squared-based dispersion.)

Table A7: Poisson Model with Entropy balance

	(1)	(2)
VARIABLES	**Poisson balance**	**Marginal effects**
Child grant recipient	0.409***	0.240***
	(0.113)	(0.0575)
Birth count in wave 1	0.0729	0.0428
	(0.0596)	(0.0356)
No of dead Children	-0.0231	-0.0136
	(0.113)	(0.0665)
Age (years)	-0.117***	-0.0684***
	(0.0110)	(0.00772)
Age at first birth (years)	0.0719***	0.0422***
	(0.0164)	(0.0101)
Years of education	-0.0123	-0.00724
	(0.0178)	(0.0104)
Married[*]	0.761**	0.446**
	(0.340)	(0.200)
Living with a partner	0.672*	0.394*
	(0.352)	(0.207)
Widow/Widower	0.655	0.384
	(0.576)	(0.339)
Unemployed Strict[**]	0.536	0.314
	(0.334)	(0.198)
Employed	-0.0388	-0.0228
	(0.117)	(0.0688)
Excellent health[***]	-0.146	-0.0858
	(0.101)	(0.0597)
Very good health	0.238	0.140
	(0.347)	(0.203)
Good health	0.276	0.162
	(0.344)	(0.202)
Fair health	0.373	0.219
	(0.346)	(0.203)
Religion (Christian)[R]	0.721*	0.423*
	(0.388)	(0.230)
Religion (Traditional)	-0.437**	-0.256**
	(0.187)	(0.114)

Religion (Muslim)	-0.425*	-0.250*
	(0.246)	(0.149)
African [C]	-0.600*	-0.352*
	(0.321)	(0.193)
Coloured	0.923*	0.542*
	(0.497)	(0.294)
Asian	0.781	0.459
	(0.509)	(0.301)
Income quintile 2[F]	-0.305	-0.179
	(0.583)	(0.343)
Income quintile 3	-0.0694	-0.0414
	(0.164)	(0.0978)
Income quintile 4	-0.0923	-0.0544
	(0.138)	(0.0831)
Income quintile 5	-0.0430	-0.0260
	(0.147)	(0.0895)
Traditional (Geographic Area) [D]	-0.0584	-0.0350
	(0.175)	(0.105)
Urban	-0.135	-0.0792
	(0.176)	(0.103)
Constant	**0.0338**	**0.0199**
	(0.181)	(0.106)
	-0.191	
	(0.817)	
Observations	**2,472**	**2,472**

[[x] Never married is the base category; [y] Unemployed Discouraged is the base category; [z] Poor health is the base category; [C] White is the base category; [D] Farms is the base category; [F] Income quintile 1 is the base category; [R] Other religious groups is the base category].
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
(Standard errors scaled using square root of Pearson chi-squared-based dispersion.)

Table A8: Poisson Model with NIDS Stratified Weights

VARIABLES	(1) Poisson Model	(2) Marginal Effects
Child grant recipient	0.476***	0.281***
	(0.0942)	(0.0557)
Birth count in wave 1	0.110**	0.0651**
	(0.0464)	(0.0274)
No of dead Children	-0.0468	-0.0277
	(0.113)	(0.0669)
Age (years)	-0.134***	-0.0790***
	(0.00860)	(0.00628)
Age at first birth (years)	0.0667***	0.0395***
	(0.0153)	(0.00900)
Years of education	0.00183	0.00108
	(0.0172)	(0.0102)
Married[*]	0.296***	0.175***
	(0.0985)	(0.0595)
Living with a partner	0.178	0.105
	(0.134)	(0.0800)
Widow/Widower	0.0537	0.0318
	(0.259)	(0.153)
Unemployed Strict[**]	0.121	0.0714
	(0.105)	(0.0624)
Employed	0.0941	0.0556
	(0.103)	(0.0611)
Excellent health[***]	0.491*	0.290*
	(0.259)	(0.154)
Very good health	0.372	0.220
	(0.254)	(0.151)
Good health	0.576**	0.340**
	(0.274)	(0.164)

Fair health	0.565*	0.334*
	(0.289)	(0.173)
Religion (Christian)[R]	-0.349**	-0.206**
	(0.135)	(0.0815)
Religion (Traditional)	-0.243	-0.144
	(0.265)	(0.158)
Religion (Muslim)	-0.417	-0.247
	(1.014)	(0.599)
African [C]	0.463	0.274
	(0.352)	(0.209)
Coloured	0.402	0.238
	(0.402)	(0.239)
Asian	-1.001	-0.591
	(1.120)	(0.662)
Income quintile 2[F]	-0.0476	-0.0292
	(0.126)	(0.0768)
Income quintile 3	-0.0467	-0.0286
	(0.120)	(0.0733)
Income quintile 4	-0.146	-0.0854
	(0.107)	(0.0640)
Income quintile 5	-0.0435	-0.0267
	(0.128)	(0.0784)
Traditional (Geographic Area) [D]	-0.123	-0.0728
	(0.152)	(0.0891)
Urban	-0.0230	-0.0136
	(0.164)	(0.0968)
Constant	**0.807**	
	(0.588)	
Observations	**2,472**	**2,472**

*Never married is the base category **Unemployed Discouraged is the base category ***Poor health is the base category [C] White is the base category [D] Farms is the base category [F] Income quintile 1 is the base category [R] Other religious groups is the base category

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

(Standard errors is calculated with the Jack-knife replication method.)

Table A9: Fixed Effect Poisson Model

VARIABLES	(1) **Fixed Effect Model**	(2) **Marginal Effects**
Child grant recipient	0.109***	0.109***
	(0.0290)	(0.0290)
No of dead Children	0.0648	0.0648
	(0.0427)	(0.0427)
Age (years)	0.0243***	0.0243***
	(0.00193)	(0.00193)
Years of education	-0.00270	-0.00270
	(0.0153)	(0.0153)
Married [x]	0.129***	0.129***
	(0.0373)	(0.0373)
Living with a partner	0.0922**	0.0922**
	(0.0426)	(0.0426)
Widow/Widower	0.129*	0.129*
	(0.0715)	(0.0715)
Unemployed Strict [y]	0.0196	0.0196
	(0.0329)	(0.0329)
Employed	0.0444	0.0444
	(0.0275)	(0.0275)
Excellent health [z]	-0.0401	-0.0401
	(0.0616)	(0.0616)
Very good health	-0.0204	-0.0204
	(0.0604)	(0.0604)

Good health	-0.0496	-0.0496
	(0.0604)	(0.0604)
Fair health	-0.0396	-0.0396
	(0.0653)	(0.0653)
Religion (Christian)[R]	0.0231	0.0231
	(0.0452)	(0.0452)
Religion (Traditional)	0.0187	0.0187
	(0.0632)	(0.0632)
Religion (Muslim)	-0.145	-0.145
	(0.302)	(0.302)
Income quintile 2[F]	-0.00159	-0.00159
	(0.0344)	(0.0344)
Income quintile 3	0.0148	0.0148
	(0.0355)	(0.0355)
Income quintile 4	-0.00976	-0.00976
	(0.0371)	(0.0371)
Income quintile 5	-0.0266	-0.0266
	(0.0469)	(0.0469)
Traditional (Geographic Area) [D]	-0.0241	-0.0241
	(0.0758)	(0.0758)
Urban	0.0358	0.0358
	(0.0712)	(0.0712)
Observations	**6,204**	**6,204**

*Never married is the base category **Unemployed Discouraged is the base category ***Poor health is the base category [C] White is the base category [D] Farms is the base category [F] Income quintile 1 is the base category [R] Other religious groups is the base category

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

(Standard errors are calculated with the Jack-knife replication method.)

Appendix B

Table B1: Balance statistics before and after entropy balancing

	Treat			Control		
Before Entropy Balancing	**Mean**	**Variance**	**Skewness**	**Mean**	**Variance**	**Skewness**
Birth count in wave 1	2.69	2.99	1.33	2.28	1.78	1.56
No of dead Children	0.18	0.24	3.15	0.16	0.18	2.75
Age (years)	31.26	55.01	0.11	35.04	58.45	-0.69
Age at first birth (years)	20.27	11.62	1.03	21.13	18.83	0.89
Years of education	8.68	11.43	-1.17	9.53	11.53	-1.43
Married	0.22	0.17	1.37	0.41	0.24	0.37
Living with partner	0.14	0.12	2.13	0.11	0.10	2.52
Widow/Widower	0.03	0.03	5.45	0.04	0.03	4.98
Divorced/Separated	0.02	0.02	7.59	0.04	0.04	4.62
Never Married	0.60	0.24	-0.40	0.40	0.24	0.41
Employed	0.35	0.23	0.64	0.57	0.25	-0.28
Unemployed Strict	0.23	0.18	1.28	0.14	0.12	2.09
Unemployed Discouraged	0.15	0.13	2.00	0.07	0.06	3.51
Health, Excellent	0.30	0.21	0.85	0.32	0.22	0.78
Health, Very Good	0.28	0.20	0.97	0.27	0.20	1.04
Health, Good	0.26	0.19	1.12	0.27	0.20	1.05
Health, Fair	0.11	0.09	2.57	0.09	0.08	2.86
Christian religion	0.87	0.11	-2.17	0.91	0.08	-2.89
Traditional Religion	0.04	0.04	4.54	0.02	0.02	6.99
Muslim Religion	0.00	0.00	41.15	0.01	0.01	10.39
No Religion	0.08	0.07	3.09	0.04	0.04	4.79
African	0.88	0.10	-2.37	0.72	0.20	-0.96
Coloured	0.11	0.10	2.44	0.19	0.15	1.58
Asian	0.00	0.00	18.34	0.03	0.03	5.42
HH Per capita Quintile 1	0.22	0.17	1.37	0.17	0.14	1.77
HH Per capita Quintile 2	0.23	0.18	1.25	0.12	0.11	2.34
HH Per capita Quintile 3	0.24	0.18	1.24	0.20	0.16	1.52
HH Per capita Quintile 4	0.09	0.09	2.76	0.37	0.23	0.56
Traditional	0.52	0.25	-0.08	0.30	0.21	0.85
Urban	0.40	0.24	0.41	0.63	0.23	-0.52

After Entropy Balancing	Mean	Variance	Skewness	Mean	Variance	Skewness
Birth count in wave 1	2.69	2.99	1.33	2.69	2.99	1.33
No of dead Children	0.18	0.24	3.15	0.18	0.24	3.15
Age (years)	31.26	55.01	0.11	31.26	55.02	0.10
Age at first birth (years)	20.27	11.62	1.03	20.27	11.62	1.03
Years of education	8.68	11.43	-1.17	8.68	11.43	-1.17
Married	0.22	0.17	1.37	0.22	0.17	1.37
Living with partner	0.14	0.12	2.13	0.14	0.12	2.13
Widow/Widower	0.03	0.03	5.45	0.03	0.03	5.45
Divorced/Separated	0.02	0.02	7.59	0.02	0.02	7.59
Never Married	0.60	0.24	-0.40	0.60	0.24	-0.40
Employed	0.35	0.23	0.64	0.35	0.23	0.64
Unemployed Strict	0.23	0.18	1.28	0.23	0.18	1.29
Unemployed Discouraged	0.15	0.13	2.00	0.15	0.13	2.00
Health, Excellent	0.30	0.21	0.85	0.30	0.21	0.86
Health, Very Good	0.28	0.20	0.97	0.28	0.20	0.97
Health, Good	0.26	0.19	1.12	0.26	0.19	1.12
Health, Fair	0.11	0.09	2.57	0.11	0.09	2.57
Christian religion	0.87	0.11	-2.17	0.87	0.11	-2.18
Traditional Religion	0.04	0.04	4.54	0.04	0.04	4.54
Muslim Religion	0.00	0.00	41.15	0.00	0.00	41.11
No Religion	0.08	0.07	3.09	0.08	0.07	3.09
African	0.88	0.10	-2.37	0.88	0.10	-2.37
Coloured	0.11	0.10	2.44	0.11	0.10	2.44
Asian	0.00	0.00	18.34	0.00	0.00	18.34
HH Per capita Quintile 1	0.22	0.17	1.37	0.22	0.17	1.37
HH Per capita Quintile 2	0.23	0.18	1.25	0.23	0.18	1.25
HH Per capita Quintile 3	0.24	0.18	1.24	0.24	0.18	1.24
HH Per capita Quintile 4	0.09	0.09	2.76	0.09	0.09	2.76
Traditional	0.52	0.25	-0.08	0.52	0.25	-0.09
Urban	0.40	0.24	0.41	0.40	0.24	0.41

Note that by construction the entropy balance measure balances the selected moments so that the weighted mean difference is zero and will not be significant.

Table B2: Distribution of treatment

		Wave5		
		0	1	
Wave1	0	766	0	766
	1	361	1,335	1,680
Total		**1,137**	**1,335**	**2,472**