



Citation for published version:

Ohrnberger, J, Fichera, E, Sutton, M & Anselmi, L 2019 'The effect of cash transfers on mental health – New evidence from South Africa' Bath Papers in International Development and Wellbeing, no. 59, Centre for Development Studies, University of Bath.

Publication date:
2019

[Link to publication](#)

University of Bath

Alternative formats

If you require this document in an alternative format, please contact:
openaccess@bath.ac.uk

General rights

Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

Take down policy

If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

**The effect of cash transfers on mental health – New evidence from
South Africa**

Julius Ohrnberger^a, Eleonora Fichera^b, Matt Sutton^a, Laura Anselmi^a

^a*Division of Population Health, Health Services Research & Primary Care, University of Manchester*

^b*Department of Economics, University of Bath*

© Julius Ohrnberger, Eleonora Fichera, Matt Sutton and Laura Anselmim 2019

All rights reserved. Attention is drawn to the fact that copyright of this working paper rests with the author and copyright of any previously published materials included may rest with third parties. A copy of this working paper has been supplied on condition that anyone who consults it understands that they must not copy it or use material from it except as permitted by law or with the consent of the author or other copyright owners, as applicable.

Published by:
The Centre for Development Studies University of Bath
Calverton Down
Bath, BA2 7AY, UK
<http://www.bath.ac.uk/cds>

ISSN 2040-••3151

Corresponding author

Julius Ohrnberger, Division of Population Health, Health Services Research & Primary Care, University of Manchester.

Email: julius.ohrnberger@manchester.ac.uk.

Series Editors:

Fariba Alamgir and James Copestake

The Centre for Development Studies at the University of Bath is an interdisciplinary collaborative research centre critically engaging with international development policy and practice.

The effect of cash transfers on mental health – New evidence from South Africa

Julius Ohrnberger, Eleonora Fichera, Matt Sutton and Laura Anselmi

Abstract

Mental health and poverty are strongly interlinked. There is a gap in the literature on the effects of poverty alleviation programmes on mental health. We aim to fill this gap by studying the effect of an exogenous income shock generated by the Child Support Grant, South Africa's largest Unconditional Cash Transfer (UCT) programme, on mental health. We use biennial data on 10,925 individuals from the National Income Dynamics Study between 2008 and 2014. We exploit the programme's eligibility criteria to estimate instrumental variable Fixed Effects models. We find that receiving the Child Support Grant improves adult mental health by 0.822 points (on a 0-30 scale), 4.1% of the sample mean. Our findings show that UCT programmes have strong mental health benefits for the poor adult population.

1 Introduction

About 1.1bn people worldwide suffer from mental health problems. There is evidence of a strong relationship between poor mental health and poverty (Lund et al., 2010), which stands in line with the social causation hypothesis that adverse socio-economic factors precede and cause mental health problems (Das et al., 2007). The link between poverty and mental health makes mental health a global development problem (Prince et al., 2007). As unconditional cash transfer (UCT) programmes are used to alleviate poverty, it is natural to investigate their effect on mental health.

One can use the Grossman model of health capital (Grossman, 1972) to hypothesise different possible effects of UCTs on mental health. Health has a dual nature in the model. It is a consumption good as it directly generates utility, but also an investment good (human capital), required for income generating activities. Based on the Grossman model, the effect of UCTs on mental health can be positive, negative, or null. The effect can be positive, as UCTs can increase household income and thus directly increase mental health investment opportunities or reduce the opportunity cost of time for mental health investment activities. Further can releasing the financial constraint have an immediate direct effect on the psychological wellbeing of household members by giving (more) financial security (Lund, 2012). However, an increase in income can also potentially lead to worse mental health outcomes through increased consumption of unhealthy goods such as alcohol and consequent worsening of and mental health in the long run (Gaarder et al., 2010). They can be ineffective as the monetary assistance provided does not enforce behavioural changes, give information or encourage investments in mental health.

There is limited and mixed evidence on the effects of UCTs on mental health (Paxson and Schady, 2010; Fernald and Hidrobo, 2011; Plagerson et al., 2011; Baird et al., 2013; Eyal and Burns, 2015; Haushofer and Shapiro, 2016; Kilburn et al., 2016). Existing studies focus on small samples of females or adolescents and fail to identify the population-wide effects of UCTs on mental health. Further are existing studies either cross-sectional or short-term analyses and do not to provide information on the long-term effects of UCTs on mental health. However, both pieces of information are important to understand for policy makers when aiming to sustainably improve mental health in LMICs (Lund et al., 2011). Our research aims to fill these

gaps in the literature.

We contribute to the literature by estimating the effects of the South African Child Support Grant (CSG) UCT programme on the mental health of a representative sample of the poor adult population from South Africa. We further extend the literature by using longitudinal data covering information about individuals up to six years which is unique in the existing literature. The CSG is South Africa's largest social cash transfer programme and a long-term UCT programme. We focus on South Africa in the analysis for the high prevalence of mental health disorders in the country, with one in six of the population suffering from depression or anxiety (Plagerson et al., 2011) and unipolar depression contributing to 5.8% of the overall burden of disease, about 1.5 times higher than for all Low- and Middle-Income Countries (LMICs) (Jack et al., 2014).

We use data from four waves (2008-2014) of the South African National Income Dynamics Study (NIDS) on 10,925 individuals living in poor households. We address selection into the CSG programme using eligibility as an instrument for grant receipt and account for unobserved individual heterogeneity in mental health by using Fixed Effects models. We find that the UCT programme improves adult mental health by 0.822 points (on a 0-30 scale) corresponding to 4.1% of the sample mean. The CSG effect on mental health is heterogeneous by gender, with only significant effects for females. Our study is the first to provide evidence on the effect of UCT programmes on adult mental health in general, showing that UCT can have strong positive effects.

2 The Child Support Grant (CSG) programme

The Child Support Grant (CSG) was introduced by the South African Government in 1998 as part of the governmental social assistance programme (South African Government, 2004). The CSG is a UCT and the South Africa's largest social cash transfer programme, targeting the poor and vulnerable population (Gomersall, 2013). The CSG aims at reducing poverty and vulnerability among children from poor socio-economic backgrounds by transferring monthly a grant to their primary caregivers, which in most cases is the biological mother of the child (Eyal and Burns, 2015).

Eligibility for programme participation is defined by two factors: (1) the age of the child; and

(2) a means test of the caregiver and his/her spouse's income and assets. The primary caregiver is defined as the main responsible person for the child and his/her daily needs (Plagerson et al., 2011). The cash transfer is substantial for poor households, as it increases household income by about 20-25% (Gomersall, 2013). The coverage of the CSG increased over time (Gomersall, 2013), as illustrated in Table 1 . Initially, only children up until the age of seven years were targeted, but the programme has been progressively extended over time to children of age up to 18 years. Before the first NIDS wave and at the time of the first NIDS wave children of age 0-14 were eligible to receive the grant. The income threshold was also lifted at a faster rate than price-inflation, from R230 (US\$17.25) to R320 (US\$24), leading to a positive real appreciation of the grant value.

Table 1 here

This makes the CSG a suitable cash transfer programme to identify the average effects of unconditional cash transfers on the poor adult population. The CSG represents a monetary shock to the average poor household in South Africa, which contains on average three to four children (Statistics South Africa, 2017). Additionally, evidence shows that although targeted at children, the transfers are shared at the household level (Delaney et al., 2008; Cluver et al., 2013) raising the possibility of within household spill-over effects on all members.

The actual receipt of the CSG ultimately depends on eligible caregiver decisions as they have to register. Selection into the programme is an important issue as children eligible and in need may miss out on the support. Recent studies show that about 27% of the eligible children have not received the grant (Gomersall, 2013). We discuss the selection problem in more detail in section 5.3.

3 The National Income Dynamics Study (NIDS)

3.1 Survey structure and coverage

We use four waves of data from the National Income Dynamics Study (NIDS; 2008-2014). The NIDS is a biennial longitudinal survey of a nationally representative sample of the South African population (Southern African Development Research Unit, 2016). A two-stage cluster sample design was used (Leibbrandt et al., 2009). Stratification was made at the district council

level and clustering was implemented by primary sampling unit (geographical areas consisting of at least one enumeration area within the district council level). The first wave of the survey was conducted between January and December 2008 and consisted of 28,226 individuals (9,605 children and 18,621 adults) from 7,296 households. The same individuals were re-interviewed and new household members were included in the following waves. We use the adult sample of the survey which includes all individuals of age 15 years and above at the time of the survey interview. We include in our analysis only individuals that are observed at least twice across waves.

Across all waves we use the lower income groups of the NIDS defined by the 2008 CSG income-eligibility lower-upper bound threshold of R800 (US\$60) per capita per month in 2008. This is the sample for which the CSG eligibility criteria are satisfied. In doing so, we use the sample of poor individuals, as the lower-upper CSG bound is close to the upper-bound of national poverty line in 2014 of R779 (US\$58) (Statistics South Africa, 2014). This sample of individuals satisfies the means-test used for CSG eligibility.

3.2 Mental Health Measure

We measure mental health using a validated 10-item version of the Centre for Epidemiological Depression Scale (CES-D) scale developed by Radloff (1977). The CES-D scale is a continuous variable that usually ranges from best to worst mental health. For ease of interpretation, we invert the scale of the CES-D ranging from zero (high depression and worst mental health status) to 30 (no depression and best mental health status).

CES-D is a robust and clinically validated measure for depression that has been widely applied in the analysis of cash transfer effects on mental health (Paxson and Schady, 2010; Fernald and Hidrobo, 2011; Haushofer and Shapiro, 2016; Kilburn et al., 2016). It is based on measures self-reported by the participants and collected in every wave of the NIDS. The CES-D scale has been used in a wide set of longitudinal studies, and it is also a validated measure for the poorer populations living in LMICs (Ali et al., 2016) and in South Africa more specifically (Baron et al., 2017).

3.3 Treatment (CSG) Variable

The explanatory variable of interest is a binary variable taking value one if an individual lives in a household in which at least one person receives the CSG grant and zero otherwise, based on individuals' reports. The average number of CSG-recipients per receiving household is 2.5, with 70 per cent of the CSG-receiving households having more than one CSG-recipient.

3.4 Control Variables

As mental health is influenced by life events (Allen et al., 2014), we add a binary variable indicating if the death of a household member had occurred in the past two years. We add a variable indicating the number of household members to control for social isolation, which is associated with poor mental health outcomes (Allen et al., 2014), and for differences in household size between CSG-receiving and non-receiving households (Delaney et al., 2008). Other variables commonly used to proxy social capital, such as social interaction or group membership, are not available throughout the waves. We include age to account for the association between age and mental health problems and age squared because of the inverted U-shape in the age distribution of wellbeing (Clark, 2007). Individuals aged 15-18 years old, are potentially eligible to receive the CSG on their own behalf. To control for any variation in mental health for this specific group, we add a binary variable indicating if the individual is aged below 19 years. We include gender, as the literature shows differences in mental health and in cash transfer programme effects on mental health by gender (Kilburn et al., 2016). We control for whether an individual is the economic decision maker responsible for investment and expenditure decisions of a household, as research has found a negative relationship between being responsible of economic decision making and perceived stress in low income settings (Mani et al., 2013).

At a community level, poor intangible assets are found to be associated with poor mental health (Wright and Kloos, 2007), we control for neighbourhood effects using a categorical variable indicating the frequency of burglary in the neighbourhood. We include a set of binary variables indicating the level of common burglary and presence of theft in the neighbourhood of the respondent (none at all, very rare, not common, fairly common or very common) and use none as base category.

Variations across the provinces of South Africa in terms of rurality and in terms of poverty are large and correlated with mental health (Lund et al., 2010; Statistics South Africa, 2014). Moreover, take-up of the CSG varies by provinces, with Gauteng and North West showing the highest exclusion of children from CSG receipt (UNICEF et al., 2016). We use a set of province binary variables using Limpopo as base category to control for the province where an individual lives in (Limpopo, Western Cape, Eastern Cape, Northern Cape, for Free State, Kwa Zulu-West, North West, Gauteng, and Mpumalanga). We also include a set of binary variables to control for whether the individual lives in a formal rural setting, a tribal authority area, or an urban formal or informal (township) setting. Controlling for rural and informal urban areas is also important as CSG-receipt is lower in these areas where individuals are less likely to sign up due to poor representation and distance to local authorities and the increased cost of travel (Delaney et al., 2008).

Individuals are also eligible to apply for other government grants alongside the CSG (South African Government, 2004). To control for any contamination effects of the other grants on the CSG effect on mental health, we add a set of four binary variables for whether the individual lives in a household that receives any of the other main support programmes (Foster Care Grant (FCG), the Disability Grant (DG), the Care Dependency Grant (CDG), or the Old Age Pension (OAP)).

4 Descriptive statistics

Tables 2a and 2b provide descriptive statistics by wave for the 10,925 individuals in the full sample. The average respondent is in moderate to poor mental health. Approximately 75% of individuals live in households receiving CSG and about 87% live in a household that is eligible to receive the CSG. This is consistent with previous studies (Delaney et al., 2008; Eyal and Woolard, 2011; Hall et al., 2012; Cluver et al., 2013; Gomersall, 2013) and is evidence of potential selection into the CSG, as in about 50% of the non-recipient households there is at least one eligible child. Every third person in the sample is male. The average respondent is 38 years old and lives with six other individuals together in a household in a moderately safe neighbourhood. About 13% of individuals in the sample are younger than 19 years of age. One in nine households has experienced the death of a household member in the past two years. 38% of the individuals report to have at least one individual in their household who receives

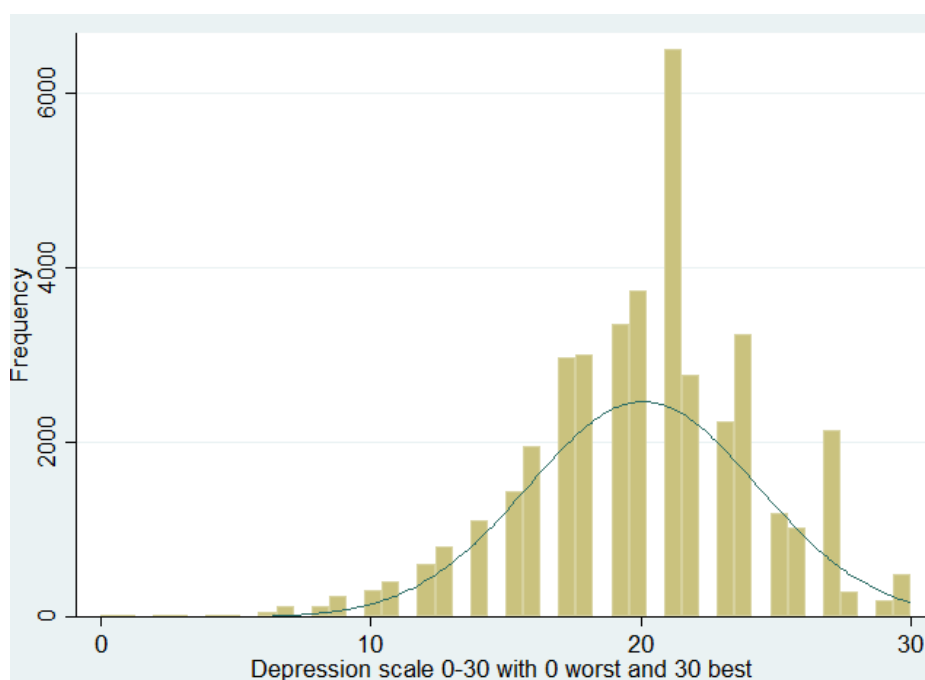
the old age pension, 12% the disability grant, 5% the foster care grant and 1% the care dependency grant.

Tables 2a and 2b here

Splitting the samples by waves shows the increase in the coverage of the CSG policy nationwide, with increasing numbers of individuals living in CSG receiving and/or in a CSG eligible household over time. Mental health improves slightly from an average of 19.0 points in 2008 to an average of 20.4 points in 2014. Table A1 discussed in section A1 of the online appendix compares individuals living in recipient and non-recipient households. We observe slightly higher CES-D scores for individuals living in receiving households, similarities in other grant receipt and disparities in household composition with more household members, more female household members and lower mean age in receiving households.

CES-D is often found in the literature to have a right-skewed (or left skewed if inverted) distribution (Radloff, 1977) leading to non-normally distributed standard errors and violating the assumptions required to implement *t*-tests. We assessed the skewness in the data by plotting the distribution of the CES-D over all waves in figure 1, showing that the CES-D is normally distributed and no transformation was needed. We also formally tested for normality and found strong support for the normal distribution of CES-D measure.

Figure 1 CES-D distribution over all waves



Source: Computation based on the sample of analysis using NIDS pooled data

5 Methods

5.1 Pooled cross-sectional model estimation

In order to investigate the association between CSG household receipt and mental health, we estimate the following OLS model:

$$(1) CES_{i,t} = \beta_0 + \beta_1 CSG_{i,t} + \mathbf{X}_{i,t}\beta_2 + \mathbf{T}_i\beta_3 + \mathbf{R}_i\beta_4 + v_{i,t},$$

where $CES_{i,t}$ is the CES-D score of the individual i in year t . $CSG_{i,t}$ is a binary variable indicating if an individual lives in a CSG-receiving household. \mathbf{X} is a vector of control variables, \mathbf{T}_i is a set of year dummies to control for time trend effects and \mathbf{R}_i is a set of regional dummy variables to control for regional variations.

We cluster standard errors on the primary sampling unit in all models because common cluster effects may occur at local level (Wittenberg, 2013). We also test for potential attrition effects in all models by including a dummy variable taking on a value of one if the individual left the survey due to death or other reasons in the following wave and zero otherwise (Verbeek and Nijman, 1992). We provide an analysis of sample attrition and sample transition (leaving the “poor” sample or moving into the “poor” sample) in section A2 of the online appendix.

5.2 Fixed Effect estimation

The OLS estimation could be downwardly biased because of potential unobserved individual heterogeneity in mental health, driven by unobservable behaviours and preferences (Hauck and Rice, 2004). We account for unobserved individual time-invariant heterogeneity in mental health using Fixed Effects (FE). By doing so, we focus on variation within individuals over time. FE address the relationship of the predictor or outcome variables with the unobserved individual component of the error term $v_{it} = a_i + u_{i,t}$. a_i is the unobservable time-invariant component and $u_{i,t}$ is the time-varying component, uncorrelated with the covariates, of the individual error term. FE account for time invariant determinants such as traumatic events, adverse childhood events or genetic health endowments which are important in shaping mental health but are not observed (Golberstein and Busch, 2014). Therefore, we formally estimate:

$$(2) CES_{i,t} = a_0 + a_1 CSG_{i,t} + X_{i,t}\alpha_2 + T_i\alpha_3 + R_i\alpha_4 + a_i + u_{i,t}$$

5.3 Instrumental Variable (IV) estimation

Selection into the CSG programme can occur for several reasons: exclusion errors occur due to lack of information about the programme, incomplete documents, distance to local authorities and related opportunity costs and travel costs, or the lack of proof of eligibility of the child's age and identity (Delaney et al., 2008; Cluver et al., 2013; Gomersall, 2013). Furthermore, individuals with poorer mental health outcomes could be less likely to apply for the grant. As a consequence, omitted variable bias can affect the estimate of the effect on mental health. Selection bias could downwardly bias the estimated treatment effects.

We address selection into the CSG programme by using an instrumental variable approach, which is an appropriate method to deal with selection due to unobservable factors (Angrist and Pischke, 2008). We instrument the binary variable of living in a CSG receiving household with a binary measure taking value one if at least one child eligible for the CSG grant lives in the household and zero otherwise. As we use a binary instrumental variable for a binary endogenous variable, we estimate the conditional Wald-Estimator (Angrist and Pischke, 2008).

Using eligibility criteria as instrumental variable for programme participation is common in the literature. For example, draft-eligibility has been used as an instrument for Vietnam war participation (Angrist and Krueger, 1991b) or school-age-eligibility has been used as an instrument for years of education (Angrist and Krueger, 1991a). Furthermore, the age-eligibility of a child has been used as instrument for CSG participation at the individual-level in a previous analysis (Eyal and Woolard, 2011).

We considered the use of alternative instrumental variables previously used in the literature as proxy for local government investment and access to government services, such as: distance to water sources from the house or dwelling, municipal expenditures in the past 30 days, household transport expenditures in the past 30 days, or the council level density of CSG receiving children, weighted by the number of council level residents. None of these instruments were strong in predicting receipt of CSG.

We use the parametric standard 2-Stage Least Squares (2SLS) estimator with both stages estimated simultaneously, first with pooled and then with FE specification and compare the results. FE 2SLS square estimation is feasible as both the instrumented and the instrumental variable vary over time. This approach has a clear strength as it allows accounting for time-invariant and time-variant unobserved individual heterogeneity simultaneously and is the preferred approach in this analysis (Le and Nguyen, 2018).

The first stage can be formalised as follows:

$$(3) \text{CSG}_{i,t} = \gamma_0 + \gamma_1 Z_{i,t} + \mathbf{X}_{i,t} \gamma_2 + \mathbf{T}_i \gamma_3 + \mathbf{R}_i \gamma_4 + a_i + u_{i,t}$$

where $Z_{i,t}$ is the instrumental variable. We use linear probability models throughout the estimation.

In the second stage we regress CES-D on the linear prediction of $\text{CSG}_{i,t}$ from the first stage and the full set of covariates $\mathbf{X}_{i,t}$.

$$(4) \text{CES}_{i,t} = c_0 + c_1 \widehat{\text{CSG}}_{i,t} + \mathbf{X}_{i,t} c_2 + \mathbf{T}_i c_3 + \mathbf{R}_i c_4 + a_i + u_{i,t}$$

c_1 is the effect of the instrumented $\text{CSG}_{i,t}$ in the first stage estimation. As in equation (4.1), \mathbf{X} is a vector of control variables, \mathbf{T}_i is a set of year dummies, \mathbf{R}_i is a set of regional dummy variables.

5.4 Instrumental variable conditions

The instrumental variable has to satisfy both the validity and the relevance conditions. Validity is satisfied when the exclusion restriction holds and the instrument affects the outcome variable only through the endogenous regressor conditional on confounders (Angrist and Krueger, 2001). The exclusion assumption is not testable. We provide the following four arguments to support it.

Firstly, the instrumental variable is coded as one for all individuals, if a child who is eligible to receive the CSG for his/her age lives in the household. This implies that individuals living with children of all other not eligible ages are coded as zero. This is crucial, as age differences around the CSG age cut-off threshold and changes of the CSG age cut –off over time are orthogonal to the outcome and unlikely to affect the outcome variable directly. For example, the age cut-off for CSG eligibility was 13 years in 2008. The assumption here is that having a child aged 13 or more does not impact mental health differently to having a child of age 12

years or less.

Secondly, we include a set of 19 binary variables indicating if children of age [0,18] live in the household of the respondent. These binary variables will pick up the effect of the instruments on mental health induced by the age of the cohabiting children. Thus, the instrumental variable should measure only the programme effects even when child-age mental health effects are present. Notably, in neither of the estimations where we control for child age effects, child effects are jointly significant in explaining adult mental health.

Thirdly, the CSG programme has time-varying age eligibility cut-offs. Due to this variation families with children of the same age have different exposures to the policy at different times. Thus, if child-age specific effects around cut-off points are present, these effects should balance out over the panel data as children of all ages become available to receive the CSG from 2012 onwards.

Fourthly, we find no statistically significant effects of child eligibility on mental health of individuals living in CSG financially ineligible households (income >R800). This finding strongly supports the assumption that changes in mental health are caused by the cash transfers and not by differences in child age. Also, after excluding from the analysis the care-taker receiving CSG, our results remain strong and significant supporting our assumption that the estimated instrumental variable effects do not reflect age effects.

The second condition, relevance, implies that the instrumental variable is correlated with the endogenous regressor and has to be uncorrelated with the error term (Angrist and Krueger, 2001). Firstly, correlation of the instrumental variable with the treatment variable at the first stage is satisfied in all first stage estimations. The correlation coefficient is always significant and shows strong magnitude in all estimations indicating that “household with a CSG eligible child” is a strong and relevant instrument for “household receives the CSG”.

Secondly, the instrumental variable is not correlated with unobservable factors of the first stage estimation. Factors that determine access to the CSG could possibly also affect the instrumental variable in the first stage estimation. We add control variables for potential confounders such as the region and province where the household lives. We use FE estimation

which allows only for time-varying factors to affect the estimation. Thus all parameters which are time-invariant such as individual preferences of adults for child birth or individual preferences to apply for the CSG are taken out of the estimation.

Thirdly, manipulation of the instrumental variable may affect the validity of the instrument leading to a bad instrument problem (Angrist and Krueger, 2001). In the context of the CSG, this would be occur if timing of birth was chosen by the poor to access CSG support.

We rule out manipulation of the instrumental variable for the following four reasons:

i) Fertility rates across South Africa are continuously falling since 1996, prior to the onset of the programme. Fertility rates fall across age-groups, provinces and population and income groups. The latest fertility report of South Africa based on the census 2011 clearly shows that fertility declined between 1996 and 2011 from 3.23 children to 2.67 children (Statistics South Africa, 2011). More recent statistical evidence shows a further fall in fertility rates to 2.55 in 2015 (Statistics South Africa, 2015).

ii) An empirical study on the effects of the CSG programme on fertility identified no difference in the odds for child birth between CSG receiving and non-receiving mothers which strongly supports the assumption of no programme induced perverse incentives of childbirth (Rosenberg et al., 2015).

iii) Data on the CSG and take-up rates suggest that especially in the first years of life of the new-born, take-up of the CSG programme is low (Cluver et al., 2013). If individuals were to have children for the sole reason to receive transfer, take-up of the programme should be high in the first years for the economic cost arising from childbirth, and for missing out on the income flow.

iv) Estimates by the United Nations in 2005 show that the cost of raising a child from age 0-17 are about \$16,000 on average for the poor population living in LMICs (UNICEF, 2005), which is about R108,540 (conversion rate 1:6.7 on average in 2005). The benefit of receiving the CSG in 2005 was R180 a month which over 17 years equals to R36,720, assuming that individuals did not anticipate increases in the monthly CSG rate. Assuming that the UN estimate is valid for South Africa, the cost of raising a child is 2.96 times as high as the benefit. This relative numbers suggest that the decision to have a child solely for the purpose of receiving the CSG grant is unlikely considering the higher cost.

A last concern of the relevance of the instrumental variable considers anticipation effects of programme receipt. Such effects can occur due to anticipation of future changes in the age-bandwidth for CSG eligibility or when household members are pregnant but not yet receiving the CSG support. To anticipate findings from the robustness analysis (placebo-estimation) with respect to this concern, we can exclude that such effects bias the instrumental variable. Following these arguments, we have strong evidence to exclude bias due to manipulation of our instrumental variable. This supports the relevance of the instrumental variable.

A key assumption of instrumental variable estimation is that individual preferences for treatment are monotonic, implying that defiers are excluded (Angrist and Pischke, 2008). When relevance, validity and monotonicity are satisfied, we estimate the Local Average Treatment Effect (LATE), which is the effect for the sub-population of treatment compliers (Angrist and Pischke, 2008). In a special case, when always-taking behaviour can be excluded, the LATE simplifies to the Average Treatment Effect on the Treated (ATET) which implies that results can be generalised to the full study population rather than to complying individuals (Angrist, 2004). This special case applies to this study as the share of “Always takers” is negligible (see table A2 in the online appendix).

5.5 Heterogeneity of the effect by gender

We investigate heterogeneous effects by gender because there is evidence of gender differences in the effect of UCT on mental health (Kilburn et al., 2016). We follow Kilburn et al. (2016) and provide sub-sample estimates of our models to make them comparable with this study.

5.6 Robustness checks

We carry out a number of robustness checks on attrition effects, on the threshold applied to identify poor (R800), on the assumption of sharing the cash grant within the household. We also carry out a placebo-treatment receipt estimation to test anticipation effects. These can also help in further identifying support for the validity of the instrumental variable.

Sample Selection

Livelihoods of individuals can improve over time, for example due to the cash transfer. As a result, they can move out of poverty over the course of the study. This group of individuals is included in the full NIDS survey but excluded from the analysis. Considering the assumptions of cash support programmes, those individuals close to the monetary eligibility threshold at the onset of the survey are likely to fall into this group (and so are the new entries which are marginally above the threshold at the onset). Ignoring potential sample selection induced by improved income for households receiving cash transfer payment can lead to a downward bias in the estimates.

Therefore, we run four sub-analyses using the instrumental variable approach with fixed effect estimation to test for sample selection. In the first sub-analysis, we keep only eligible individuals from wave one and estimate the model for all years using this reduced sample. This can give us an idea if my findings are robust to drop-outs enforced by applying the selected threshold. In a second approach, we estimate the model with the full sample, including all income groups to test robustness of the cash transfer effects on mental health across the full population. Finally, we use the full balanced panel sample irrespective of income group and in the fourth model we use the balanced sample of my preferred study sample. The third and fourth sub-analyses address concerns regarding attrition as balanced panel samples suffer most from selection bias, if a bias is present (Wooldridge, 2001).

Excluding the recipient of the cash transfer

A core assumption of the study is that cash transfers received by care takers are shared on a household level. We test this assumption by re-estimating our models excluding those individuals who are cash transfer recipient within the household. We would expect the coefficient associated with receiving CSG to be unchanged if cash transfers were shared within the household.

Placebo treatment estimation

Another robustness check addresses the differences in characteristics of households receiving and non-receiving the cash transfer. We run a set of placebo-estimations to understand if these conditional variations matter and how independent the effect of the cash transfer is for mental health. We use a reduced sample size in this analysis composed as follows: at the time

of the comparison, in wave 1-3 neither household receives the cash transfer but a sub-set of households will receive the transfer in wave 4. We use a dummy variable which identifies individuals living in households that will receive the cash transfer at wave 4 but who have not received the CSG in any previous wave as “1” and “0” otherwise. We compare never receivers with receivers only in the final wave, wave four, but estimate this model using data on the balanced sample on the first three waves. We define treated individuals as those who receive CSG in any of the waves, while the never-receivers are defined as untreated.

We undertake three estimations, first a pooled cross-sectional analysis over the first three waves, second an instrumental variable analysis over the first three waves and finally an instrumental variable analysis over all four waves. The instrument is the binary variable indicating if the individual lives in a household with a child of CSG eligible age. Non-significance of the placebo-dummy in the first and second estimation would imply that the cash transfer and the instrumented cash transfer are truly exogenous to household characteristics and affects mental health whilst controlling for confounders. Significance in the third estimation would further support the causal effect of the cash transfer on mental health outcomes. Non-significance would also imply that no anticipation effect for the cash transfer programme occurs, which would further support the validity of the instrumental variable.

Using non-eligible to test treatment causality

A last robustness test is directed at the causality of the cash transfer effect on mental health. We use a “placebo” sample of individuals living in household that are not-eligible to receive the CSG because household income is above the threshold of Rand800 per capita. We use all four waves in a fixed effect estimation of mental health on our instrumental binary variable “individual lives with a CSG age eligible child” while controlling for covariates. A statistically significant effect of the dummy variable on mental health would imply that the age of the child indeed affects mental health directly even though households are not eligible to receive CSG. No statistically significant effect would support the assumption that CSG affects mental health because of the cash transfer and not because of the age of the child. We further use descriptive analysis on attrition and sample transition. We present the discussion of the analysis in the appendix in section A2.

6 Results

6.1 Pooled versus Fixed Effects

Table 3 reports the results of the pooled and FE estimation. We find a positive and significant effect on mental health for individuals living in a CSG receiving household across the models. In the pooled model without covariates in column (1), individuals living in a CSG receiving household have on average a 0.325 point higher CES-D score than individuals living in non-recipient households.

Table 3 here

When adding all covariates to the pooled model in column (2) the coefficient increases to 0.405. This implies a 2% increase in CES-D score compared to the mean of CES-D. When controlling for unobserved heterogeneity in the models using FE without and with covariates in columns (3) and (4), results show that the size of the coefficient increases and it remains statistically significant. This indicates a downward bias in the pooled OLS estimate due to correlation of the main explanatory variable with unobservable idiosyncratic factors. The coefficient size reported in column (4) is 0.536, which indicates a 2.7% increase in CES-D from the mean of CES-D.

In both the pooled and FE models, being younger than 19 years old is associated with better mental health. In the FE model age has a positive non-linear association with mental health. Males have on average a significantly better mental health than females in the pooled model. In the pooled model, age has a non-linear, and positive above 30 years, association with mental health. In the pooled model, mental health is better in households of larger size. Economic decision making and negative events are both negatively associated with mental health.

Notably, attrition is significantly and negatively associated with transfer receipt in the pooled model in column (2). However, when using FE estimation this association loses statistical significance which tells us that FE address the correlation of attrition with unobservable factors determining mental health.

We perform a Hausman test to determine if FE or Random Effects models should be used. The Hausman test rejects the null hypothesis $p < 0.001$ in favour of the FE estimation.

6.2 2SLS and 2SLS FE estimation

The estimates of the first stage regression of the different instrumental variable models are presented in Table 4, for the whole population in columns (1) to (4) including pooled OLS without and with covariates and FE estimations without and with covariates, and FE estimation for male and female separately in columns (5) and (6). The regression of the household level CSG receipt on the instrumental variable in the top row of the table shows positive significant effects throughout all specifications.

[Table 4 here](#)

The magnitude of the coefficient of the instrumental variable varies over the specifications with highest magnitude for the 2SLS estimation without covariates (0.833). Adding covariates to the OLS estimation in model (2) reduces the coefficient to 0.723, indicating correlation of the instrumental variable with other factors. When using FE with 2SLS estimation without covariates, the magnitude is further reduced to 0.712, which indicates that FE account for unobservable constant factors. Adding covariates in model (4) to the FE estimation further reduces the magnitude of the coefficient to 0.644. The estimated coefficient gives the compliance rate for the group of transfer recipients with the instrumental variable. The compliance rate shown in model (1) is 83%, which implies that 83% of the recipients comply in their treatment status conditional on the instrumental variable.

Table 5 presents the findings of the second stage of the pooled and FE instrumental variable estimations for the same six models. The coefficient associated with the CSG is positive and significant in all models, except for the one estimated on the male sub-sample where it is not statistically significant ($p = 0.392$).

[Table 5 here](#)

In column (1) the effect of living in a receiving CSG household on mental health outcome, estimated using pooled 2SLS, increases mental health by about half a unit on the CES-D scale

(0.614) compared to individuals living in non-receiving household. The magnitude of the effect is higher (0.749) in model (2) when controlling in the pooled 2SLS estimation for confounding factors in the determining mental health. The FE 2SLS estimation in column (3) shows a marginally larger magnitude compared to the 2SLS with a coefficient of size 0.621 which is a 15% standard deviation increase in mental health. The marginally larger size of the coefficient in column (3) compared to column (1) shows that the 2SLS estimation without covariates in (1) is downwardly biased due to unobserved heterogeneous factors.

Adding control variables in the FE 2SLS estimation in column (4) shows a transfer effect of size 0.822 on individuals' mental health which is a 4.1% improvement in the mean value of mental health. The 2SLS coefficient of transfer receipt without FE shows low variation with and without conditioning on covariates whereas in the 2SLS estimation with FE it shows significant difference conditioning on covariates and without covariates. An explanation is that covariates are correlated with unobservable factors adding bias to the estimation, which we address by using individual FE model. The CSG effect is not significant for the male sub-sample in column (5) and the strongest cash transfer effect amongst all models is observed in the female sub-sample in column (6) with an improvement on the CES-D scale of one unit or an increase in mental health of five per cent.

The FE 2SLS model with covariates in column (4) is twice the size of the pooled model coefficient in column (2) of table 3, indicating a potential downwardly bias of the pooled model-coefficient due to unobserved heterogeneity in mental health. The bias remains when controlling for unobserved heterogeneity in health but not instrumenting for the treatment receipt as the coefficient size of the FE in column (4) of table 3 is still 0.3 points lower than the one estimated with FE 2SLS in column (4) of table 5.

When controlling for determinants of mental health, the following coefficients estimated with the pooled 2SLS in column (2) are associated with mental health. We find positive significant effects for being under 19 years of age, being male and the size of the household. Significant negative associations for age (though with increasing positive non-linear age effects), being in charge of economic decision making, death in household and attrition. The attrition dummy is only significant in the pooled model. This indicates for the FE models that individuals who leave the survey for reasons of death or non-response are not systematically biasing the

estimation.

We find in the FE model in column (4), positive significant associations with age. Both FE models in columns (4) and (5) show a positive effect of being under 19 years of age on mental health. The FE model for males in column (5) shows positive effects of negative events on male mental health. In contrast the FE model for females in column (6) identifies negative associations of negative events with mental health.

We test the power of our instrumental variable and find strong support for using the instrumental variable “individual lives in a household with a CSG-age eligible child”. We provide a detailed overview of the test findings in section A2 of the online appendix.

6.3 Robustness checks

We present the analysis of sample selection effects in table 6 and attrition in table 7. In table 8 and table 9, we present the analysis of the cash transfer effect on mental health without the care taking recipient(s) in the household and the placebo analysis of instrumented and non-instrumented cash transfer receipt. Table 10 presents a last supporting test on the exclusion assumption of the instrumental variable.

The robustness analysis regarding the sample composition (tables 6 and 7) shows that the selection model is robust to changes in the margin and to transition in income, as the coefficient associated with being a CSG recipient remains statistically significant and of similar magnitudes in all models. When estimating the IV model on the balanced panel, the results are qualitatively unaffected, indicating again that attrition due to death or non-response does not bias our sample estimation.

Table 8 presents the results from the first stage of the 2SLS estimation on the sample excluding the individual in CSG-recipient households in columns (1), of the placebo-sample test over the first three waves in column (2) and of the placebo sample with all four waves in column (3). The instrumental variable is valid for the reduced sample in column (1) and not significant in column (2). This indicates that the instrumental variable is tracking changes and variations in CSG recipients correctly, as none of the individuals receive the CSG over the first three waves. Using the placebo sample on all four waves, the instrumental variable is significant as

expected.

In table 9, estimates of the second stage of the sample excluding the care taking individuals receiving the CSG-recipient(s) in model (1) show a significant strong effect of the instrumental variable on mental health (1.220). This finding supports the argument that the cash transfer is shared within the household among the household members and not only kept and used by the actual recipient(s). In model (2), which shows the results of the first three waves pooled cross-sectional OLS regression on the actual binary “last wave CSG”, no significant effect is associated with being future CSG recipients and mental health. No significant effect is observed in model (3), using the instrumental variable approach over the first three waves. In model (4), we find a strong significant positive effect (6.5) of the cash transfer on mental health when the placebo-recipients actually receive the cash transfer in the final round compared to the never-recipients. These findings support the causality of the cash transfer effect on mental health and the validity of the instrumental variable against possible anticipation effects.

Table 10 presents the estimation of the effect of mental health on child CSG age eligibility, using the all waves with individuals living in financially non-eligible households. The binary instrumental variable indicating if an individual lives with a CSG age eligible child has no significant effect on mental health. This further supports our claim of no effects of child age eligibility on adult mental health and overall the exclusion assumption of the chosen instrumental variable.

Our robustness analysis shows that our results are robust to sample selection and attrition effects, that mental health effects remain strong when actual cash transfer recipients are excluded from the sample estimation, and that no placebo-effects of cash transfer receipt occur. We also find further strong support for the exclusion assumption (e.g. validity) of the instrumental variable to hold as living with a child in the CSG age-eligibility bracket in non-poor households has no statistical significant effect on mental health. We further show using a descriptive analysis that transition and attrition effects do not bias the sample composition, see appendix section A2 for a discussion of these results.

7 Discussion and conclusion

This is the first study to analyse the effect of a large unconditional cash transfer programme, the South African Child Support Grant, on mental health of adults, rather than specific population sub-groups, living in poverty. We use a large longitudinal sample of 10,925 individuals from four waves (2008-2014) of the National Income Dynamics Study, a representative survey of the South African population. Using a Fixed Effect instrumental variable approach to account for potential selection bias into the CSG, we find that the cash transfer has a strong positive effect on mental health of individuals living in recipient households on average by half a unit on a 30-point scale. We conducted sub-analyses by gender and found a significant effect, only for females, twice the size of the male coefficient. We find our results robust to potential attrition, sample selection and placebo-effects.

The finding of positive effects of an unconditional cash transfer on mental health fits into the behavioural economics and psycho-social literature on the relationship between poverty and mental health conditions (Lund, 2012). It is also in line with findings from studies analysing the short term effects of unconditional cash transfer programmes on mental health on sub-populations from LMICs (Plagerson et al., 2011; Baird et al., 2013; Eyal and Burns, 2015; Haushofer and Shapiro, 2016).

Previous work on the effect of a UCT effect on adolescent mental health found different disparities with significant effects only for males (Kilburn et al., 2016). The difference in findings can be explained by the different design of the cash transfer programmes. Kilburn et al. (2016) used a UCT with a short term horizon whereas the CSG is a long term support programme. Differences can also occur due to the different sample populations. Kilburn et al. (2016) used a sample of adolescents whereas our analysis contributed by using an adult sample. Our findings of significant effects fit into the epidemiological literature on the burden of mental health among the females. Female mental health is possibly more responsive to the UCT as women are at higher risk for common mental health disorders with 50% higher prevalence of depression for women (World Health Organization, 2008).

The main challenge of this paper is that the programme is not randomly assigned. Our

instrumental variable approach with Fixed Effects accounts for selection effects. The advantage of using a natural experiment like the CSG is the external validity of its implication for studying the mental health effects of cash transfer programmes. Our chosen instrumental variable, “household contains an eligible child”, is strong and valid in explaining cash transfer receipt. This instrumental variable varies exogenously over time because of the changes to the eligibility threshold making it stronger than a simple cross-section with a single eligibility criterion. Furthermore, we conducted several tests to support the validity and exclusion assumption of the instrumental variable.

The aim of this study was to understand the effects of an UCT on mental health of the average poor adult population. Due to the design of the CSG, which requires a household to have an age-eligible child to receive the cash transfer, results may be representative of households with an eligible children, rather than a South African household. However, this is an unlikely concern for the composition of poor households in South Africa. In the average poor South African household live between three and four children, where children are defined as household members below age 18 (Statistics South Africa, 2017).

The finding highlights that unconditional cash transfer programmes have strong and robust direct positive benefits for mental health of adult populations from LMICs. Following the Grossman model of health where more healthy time is an input factor of individual productivity (Grossman, 1972), better mental health can enable individuals to improve their productivity which can then contribute to decrease poverty in the long-term. The effects of better mental health could possibly show strong spill-over effects on other dimensions, especially when considering the strong co-morbidities of mental with physical health and the strong relationship of mental health with poverty (Lund et al., 2010; Ohrnberger et al., 2017). In the South African context, population wide improvements in mental health could show significant effects on HIV-prevalence, due to the strong positive correlation between the two (Lund et al., 2012).

Acknowledgements

The NIDS was developed by a team of researchers from Southern Africa Labour and Development Research Unit based at the University of Cape Town's School of Economics. Responsibility for interpretation of the data and any errors is the authors' alone.

Funding statement

This work has been produced as part of the corresponding author's PhD programme at the University of Manchester. The PhD programme was funded by the President's Doctoral Scholar Award of the University of Manchester.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Data availability statement

The NIDS data sets used for this study are publicly available at <http://www.nids.uct.ac.za/nids-data/data-access>

References

Ali, G.-C., Ryan, G. and De Silva, M. J. (2016) 'Validated Screening Tools for Common Mental Disorders in Low and Middle Income Countries: A Systematic Review.' *Plos One*, 11(6).

Allen, J., Balfour, R., Bell, R. and Marmot, M. (2014) 'Social determinants of mental health.' *International Review of Psychiatry*, 26(4) pp. 392–407.

Angrist, J. D. (2004) 'Treatment Effect Heterogeneity in Theory and Practice.' *The Economic Journal*, 114(2002) pp. 52–84.

Angrist, J. D. and Krueger, A. (1991a) 'Does Compulsory School Attendance Affect Schooling and Earnings?' *The Quarterly Journal of Economics*, 106(4) pp. 979–1014.

Angrist, J. D. and Krueger, A. (1991b) *Estimating the payoff to schooling using the vietnam-era draft lottery*. (NBER Working Paper).

Angrist, J. D. and Krueger, A. B. (2001) 'Instrumental Variables and the Search for Identification: From Supply and Demand to Natural Experiments.' *Journal of Economic Perspectives*, 15(4) pp. 69–85.

Angrist, J. D. and Pischke, J.-S. (2008) *Mostly harmless econometrics: An empiricist's companion*. Princeton University Press.

Baird, S., de Hoop, J., Ozler, B., Hoop, J. De and Özler, B. (2013) 'Income Shocks and Adolescent Mental Health.' *Journal of Human Resources*, 48(2) pp. 370–403.

Baron, E. C., Davies, T. and Lund, C. (2017) 'Validation of the 10-item Centre for Epidemiological Studies Depression Scale (CES-D-10) in Zulu, Xhosa and Afrikaans populations in South Africa.' *BMC Psychiatry*. *BMC Psychiatry*, 17(1) pp. 1–14.

Clark, A. E. (2007) *Born To Be Mild? Cohort Effects Don't (Fully) Explain Why Well-Being is U-Shaped in Age*. (IZA Discussion paper series).

Cluver, L., Boyes, M., Orkin, M., Pantelic, M., Molwena, T. and Sherr, L. (2013) 'Child-focused state cash transfers and adolescent risk of HIV infection in South Africa: a propensity-score-matched case-control study.' *The Lancet Global Health*, 1(6) pp. 362–370.

Das, J., Do, Q.-T., Friedman, J., McKenzie, D. and Scott, K. (2007) 'Mental health and poverty in developing countries: Revisiting the relationship.' *Social Science and Medicine*, 65(3) pp. 467–480.

Delaney, A., Ismail, Z., Graham, L. and Ramkissoon, Y. (2008) *Review of the Child Support Grant: Uses, Implementation and Obstacles*. (United Nations Children's Fund Report).

Eyal, K. and Burns, J. (2015) *Up or Down? Intergenerational Mental Health Transmission and Cash Transfers in South Africa*. (Working Paper).

Eyal, K. and Woolard, I. (2011) *Throwing the Book at the CSG*. (Southern Africa Labour and Development Research Unit Working Paper Series).

Fernald, L. C. H. and Hidrobo, M. (2011) 'Effect of Ecuador's cash transfer program (Bono de Desarrollo Humano) on child development in infants and toddlers: A randomized effectiveness trial.' *Social Science and Medicine*, 72(9) pp. 1437–1446.

Gaarder, M. M., Glassman, A. and Todd, J. E. (2010) 'Conditional cash transfers and health: unpacking the causal chain.' *Journal of Development Effectiveness*, 2(1) pp. 6–50.

Golberstein, E. and Busch, S. (2014) 'Mental Health, Determinants of.' *Encyclopedia of Health Economics*. 1st ed., Elsevier.

Gomersall, J. (2013) 'The performance of the Child Support Grant: Review and research priorities.' *Development Southern Africa*, 30(4-05) pp. 525–544.

Grossman, M. (1972) 'Concept of Health Capital and Demand for Health.' *Journal of Political Economy*, 80(2) pp. 223–225.

Hall, K., Woolard, I., Lake, L. and Smith, C. (2012) *South African Child Gauge*. (Children's Institute Annual Report, University of Cape Town).

Hauck, K. and Rice, N. (2004) 'A longitudinal analysis of mental health mobility in Britain.' *Health Economics*, 13(10) pp. 981–1001.

Haushofer, J. and Shapiro, J. (2016) 'The short-term impact of unconditional cash transfers to the poor: experimental evidence from Kenya.' *Quarterly Journal of Economics*, 131(4) pp. 1973–2042.

Jack, H., Wagner, R. G., Petersen, I., Thom, R., Newton, C. R., Stein, A., Kahn, K., Tollman, S. and Hofman, K. J. (2014) 'Closing the mental health treatment gap in South Africa: a review of costs and cost-effectiveness.' *Global Health Action*, 7 pp. 1–11.

Kilburn, K., Thirumurthy, H., Halpern, C. T., Pettifor, A. and Handa, S. (2016) 'Effects of a Large-Scale Unconditional Cash Transfer Program on Mental Health Outcomes of Young People in Kenya.' *Journal of Adolescent Health*, 58(2) pp. 223–229.

Le, H. T. and Nguyen, H. T. (2018) 'The impact of maternal mental health shocks on child health - Estimates from Fixed-Effects Instrumental Variables Models for Two Cohorts of Australian Children.' *American Journal of Health Economics*, 4(2) pp. 185–225.

Leibbrandt, M., Woolard, I. and De Villiers, L. (2009) *Methodology : Report on NIDS Wave 1*. Southern African Labour & Development Research Unit.

Lund, C. (2012) 'Poverty and mental health: a review of practice and policies.' *Neuropsychiatry*, 2(3) pp. 213–219.

Lund, C., Breen, A., Flisher, A. J., Kakuma, R., Corrigall, J., Joska, J. A., Swartz, L. and Patel, V. (2010) 'Poverty and common mental disorders in low and middle income countries: A systematic review.' *Social Science & Medicine*, 71(3) pp. 517–528.

Lund, C., Petersen, I., Kleintjes, S. and Bhana, A. (2012) 'Mental Health Services in South Africa: Taking stock.' *African Journal of Psychiatry*, 15(6) pp. 402–405.

Mani, A., Mullainathan, S., Shafir, E. and Zhao, J. (2013) 'Poverty impedes cognitive function.' *Science*, 341(6149) pp. 976–80.

Ohrnberger, J., Fichera, E. and Sutton, M. (2017) 'The dynamics of physical and mental health in the older population.' *Journal of the Economics of Ageing*, 9 pp. 52–62.

Paxson, C. and Schady, N. (2010) 'Does Money Matter? The Effects of Cash Transfers on Child Health and Development in Rural Ecuador.' *Economic Development and Cultural Change*, 59(1) pp. 187–229.

Plagerson, S., Patel, V., Harpham, T., Kielmann, K. and Mathee, A. (2011) 'Does money matter for mental health? Evidence from the Child Support Grants in Johannesburg, South Africa.' *Global Public Health*, 6(7) pp. 760–776.

Prince, M., Patel, V., Saxena, S., Maj, M., Maselko, J., Phillips, M. R. and Rahman, A. (2007) 'No Health Without Mental Health.' *The Lancet*, 370 pp. 859–877.

Radloff, L. (1977) 'The CES-D scale: A self report depression scale for research in the general population.' *Applied Psychological Measures*, 1 pp. 385–401.

Rosenberg, M., Pettifor, A., Nguyen, N., Westreich, D., Bor, J., Bilyuzhnikova, T., Mee, P., Twine, R., Tollman, S. and Kahn, K. (2015) 'Relationship between receipt of a social protection grant for a child and second pregnancy rates among South African women: A cohort study.' *PLoS ONE*, 10(9) pp. 1–12.

South African Government (2004) *Social Assistance Act, 2004*.

Southern African Development Research Unit (2016) *Wave 4 Overview National Income Dynamics Study*.

Statistics South Africa (2011) *Fertility in South Africa - Census 2011*.

Statistics South Africa (2014) *Poverty Trends in South Africa*.

Statistics South Africa (2015) *Mid-year population estimates 2015*.

Statistics South Africa (2017) *Poverty Trends in South Africa: An examination of absolute poverty between 2006 and 2015*. Statistics South Africa.

UNICEF (2005) *The State of the World ' S Children 2005 - Childhood Under Threat*. (United Nations Children's Fund Report).

UNICEF, DSD and SASSA (2016) *Removing Barriers To Accessing Child Grants*.

Verbeek, M. and Nijman, T. (1992) 'Testing for Selectivity Bias in Panel Data.' *International Economic Review*, 33(3) pp. 681–703.

Wittenberg, M. (2013) 'A comment on the use of " cluster " corrections in the context of panel data.' *National Income Dynamics Study*.

World Health Organization (2008) *The global burden of disease: 2004 update*.

Wright, P. A. and Kloos, B. (2007) 'Housing environment and mental health outcomes: analysis perspective.' *Journal of Environmental Psychology*, 27(1) pp. 79–89.

Tables

Table 1 Child Support Grant age and income eligibility criteria and grant value between 1998 and 2014

Legislation date	Eligible age (years)	Income threshold (South African Rand per month)	Grant amount (South African Rand per month)
01/10/1998	0-7		R 100
01/07/1999	0-7		R 100
01/07/2000	0-7	R 800 in Rural Areas;	R 100
01/07/2001	0-7	R 1,100 in Urban Areas	R 110
01/04/2002	0-7		R 140
01/10/2002	0-7		R 160
01/04/2003	0-9	Unchanged until October 2008	R 160
01/04/2004	0-11		R 170
01/04/2005	0-14		R 180
01/04/2006	0-14		R 190
01/04/2007	0-14		R 200
01/04/2008	0-14		R 210
01/10/2008	0-14	R 2,300	R 230
01/01/2009	0-15	R 2,400	R 240
01/04/2010	0-16	R 2,500	R 250
01/04/2011	0-17	R 2,600	R 260
01/01/2012	0-18	R 2,800	R 280
01/04/2013	0-18	R 2,900	R 290
01/04/2014	0-18	R 3,100	R 310
01/10/2014	0-18	R 3,200	R 320

Source: (Eyal and Burns, 2015): Notes: A.) Age refers to the upper age limit. B.) The income threshold for CSG eligibility was defined as 10 times the grant amount in October 2008 to adjust for constantly increasing price-inflation. C.) If the primary caregiver is married, the income threshold is doubled, for instance to R 6,400 per month in October 2014.

Table 2a Summary statistics 2008-2014

Variables	Definition	2008 n=6,801	2010 n=7,831	2012 n=7,818	2014 n=6,323	All years n=10,925
<u>Outcome Variable</u>						
CES-D	Centre for Epidemiological Depression Scale ranging from 0-30; higher values indicate better mental health	18.99 (4.39)	20.07 (4.00)	20.12 (4.28)	20.36 (4.04)	19.90 (4.21)
<u>Main Explanatory Variable</u>						
Household CSG	1 if individual lives in a CSG- receiving household, 0 otherwise	0.65	0.76	0.80	0.83	0.76
<u>Instrumental variable</u>						
Household with CSG eligible child	1 if a child eligible for the CSG lives in the household, 0 otherwise (including no children)	0.83	0.87	0.90	0.89	0.87
<u>Covariates</u>						
Male	0 if female, 1 if male	0.32	0.34	0.32	0.29	0.32
Age	The age of the individual in years	37.58 (17.64)	37.86 (18.18)	38.61 (18.00)	40.96 (17.69)	38.68 (17.94)
Age under 19	1 if the individual is <19 years of age, 0 otherwise	0.17	0.16	0.13	0.05	0.13
Econ. decision maker	1 if the individual is the economic decision maker of the household, 0 otherwise	0.39	0.39	0.41	0.46	0.41
Size of the household	The number of household members	5.91 (3.17)	6.62 (3.82)	6.60 (3.79)	6.55 (3.53)	6.43 (3.61)
Death in household	1 if a household member has died in the past two years, 0 otherwise	0.18	0.16	0.14	0.12	0.15
Household OAG	1 if individual lives in an Old Age Pension -receiving household, 0 otherwise	0.32	0.41	0.39	0.41	0.38
Household DG	1 if individual lives in a DG-receiving household, 0 otherwise	0.15	0.10	0.11	0.12	0.12
Household FCG	1 if individual lives in a FCG-receiving household, 0 otherwise	0.04	0.05	0.06	0.06	0.05
Household CDG	1 if individual lives in a CDG-receiving household, 0 otherwise	0.01	0.01	0.02	0.02	0.01
Neighbourhood Theft	0"never happens in neighbourhood", 1"very rare in neighbourhood", 2"not common in neighbourhood", 3"fairly common in neighbourhood", 4" very common in neighbourhood"	1.88 (1.49)	1.84 (1.38)	2.26 (1.43)	2.21 (1.48)	2.05 (1.45)

Note: Descriptive statistics are on the sample of the estimated models. n indicates the number of individuals. Variable means (standard deviations when applicable).

Table 2b Summary statistics 2008-2014

Variables	Definition	2008 n=6,801	2010 n=7,831	2012 n=7,818	2014 n=6,323	All years n=10,925
Region	The base category is "Rural formal"					
Tribal Authority Area	1 if the individual lives in a tribal authority area, 0 otherwise	0.53	0.54	0.56	0.55	0.54
Urban Formal	1 if the individual lives in an urban formal area, 0 otherwise	0.31	0.30	0.29	0.29	0.30
Urban Informal (Townships)	1 if the individual lives in an urban informal area, 0 otherwise	0.07	0.07	0.07	0.07	0.07
Province	The base category is "Limpopo"					
Western Cape	1 if the individual lives in Western Cape, 0 otherwise	0.08	0.07	0.08	0.07	0.07
Eastern Cape	1 if the individual lives in Eastern Cape, 0 otherwise	0.14	0.14	0.14	0.14	0.14
Northern Cape	1 if the individual lives in Northern Cape, 0 otherwise	0.08	0.07	0.06	0.06	0.07
Free State	1 if the individual lives in Free State, 0 otherwise	0.06	0.05	0.05	0.05	0.06
KwaZulu-West	1 if the individual lives in KwaZulu-West, 0 otherwise	0.33	0.34	0.35	0.38	0.35
North West	1 if the individual lives in North West, 0 otherwise	0.08	0.08	0.07	0.06	0.07
Gauteng	1 if the individual lives in Gauteng, 0 otherwise	0.06	0.06	0.07	0.07	0.06
Mpumalanga	1 if the individual lives in Mpumalanga, 0 otherwise	0.07	0.07	0.07	0.07	0.07

Note: Descriptive statistics are on the sample of the estimated models. n indicates the number of individuals. Variable means (standard deviations when applicable).

Table 3 Effect of CSG on mental health: Pooled OLS and Fixed Effect estimation

	(1) Pooled OLS without covariates	(2) Pooled OLS with covariates	(3) FE without covariates	(4) FE with covariates
Household CSG	0.325*** (0.087)	0.405*** (0.091)	0.449*** (0.119)	0.536*** (0.126)
Male		0.346*** (0.051)		
Age		-0.076*** (0.009)		0.136* (0.080)
Age Squared		0.001*** (0.000)		0.001 (0.000)
Age under 19		0.513*** (0.097)		0.385** (0.169)
Economic decision maker		-0.143** (0.061)		0.037 (0.082)
Household Size		0.048** (0.022)		0.045 (0.038)
Negative Event		-0.215** (0.094)		-0.048 (0.116)
Neighbourhood Theft		-0.036 (0.030)		0.034 (0.035)
Attrition		-0.194** (0.098)		0.014 (0.132)
Constant	18.778*** (0.122)	21.323*** (0.324)	18.759*** (0.131)	12.149*** (3.031)
Year	YES	YES	YES	YES
Other Government Programmes	No	YES	No	YES
Child Age Dummy	No	YES	No	YES
Province	No	YES	No	YES
Region	No	YES	No	YES
Observations	28,773	28,773	28,773	28,773
Individuals			10,925	10,925
R-squared	0.016	0.066	0.020	0.025

The outcome variable is CES-D (0-30) the measure for depression; PSU clustered standard errors are in parenthesis; *** p<0.01, ** p<0.05, * p<0.1.

Table 4 Effect of eligibility on CSG receipt: First Stage 2SLS, Fixed effect 2SLS estimation

	(1)	(2)	(3)	(4)	(5)	(6)
	First Stage 2SLS without covariates	First Stage 2SLS with covariates	First Stage FE without covariates	First Stage FE with covariates	First Stage FE Male	First Stage FE Female
CSG eligible child	0.833*** (0.006)	0.723*** (0.011)	0.712*** (0.014)	0.644*** (0.016)	0.636*** (0.022)	0.643*** (0.017)
Male		-0.021*** (0.004)				
Age		0.001 (0.001)		0.011** (0.005)	0.002 (0.011)	0.014** (0.006)
Age Squared		-0.000** (0.000)		-0.000* (0.000)	0.000 (0.000)	-0.000*** (0.000)
Age under 19		-0.007 (0.007)		0.012 (0.011)	-0.003 (0.018)	0.017 (0.014)
Economic decision maker		0.003 (0.005)		-0.001 (0.005)	-0.000 (0.012)	-0.002 (0.007)
Household Size		-0.001 (0.003)		0.010*** (0.003)	0.014*** (0.004)	0.008*** (0.003)
Negative Event		-0.010 (0.008)		0.005 (0.009)	0.002 (0.014)	0.007 (0.009)
Neighbourhood Theft		0.003 (0.002)		-0.001 (0.002)	-0.002 (0.003)	0.000 (0.003)
Attrition		-0.010 (0.008)		-0.005 (0.009)	0.013 (0.012)	-0.014 (0.011)
Constant	-0.038*** (0.007)	-0.040 (0.026)				
Year	YES	YES	YES	YES	YES	YES
Other Government Support	NO	YES	NO	YES	YES	YES
Child Age Dummy	NO	YES	NO	YES	YES	YES
Province	NO	YES	NO	YES	YES	YES
Region	NO	YES	NO	YES	YES	YES
Observations	28,773	28,773	28,773	28,773	9,147	19,626
Individuals			10,925	10,925	3,723	7,202
R-squared	0.443	0.482	0.277	0.305	0.349	0.286

The outcome variable is a binary variable indicating if the individual lives in a CSG-receiving household or not; PSU clustered standard errors are in parenthesis; *** p<0.01, ** p<0.05, * p<0.1.

Table 5 Effect of CSG on mental health: Second Stage 2SLS, Fixed Effect 2SLS

	(1) 2SLS without covariates	(2) 2SLS with covariates	(3) FE 2SLS without covariates.	(4) FE 2SLS with covariates	(5) FE 2SLS Male	(6) FE 2SLS Female
Household CSG	0.614*** (0.125)	0.749*** (0.152)	0.621*** (0.231)	0.822*** (0.279)	0.468 (0.447)	1.000*** (0.323)
Male		0.368*** (0.051)				
Age		-0.077*** (0.009)		0.133* (0.080)	0.087 (0.146)	0.146 (0.092)
Age Squared		0.001*** (0.000)		0.001* (0.000)	-0.001 (0.001)	0.001** (0.000)
Age under 19		0.517*** (0.098)		0.380** (0.169)	0.734** (0.288)	0.143 (0.214)
Economic decision maker		-0.135** (0.061)		0.041 (0.082)	-0.073 (0.156)	0.028 (0.110)
Household Size		0.053** (0.022)		0.042 (0.037)	0.014 (0.067)	0.057 (0.039)
Negative Event		-0.208** (0.094)		-0.050 (0.115)	0.386** (0.161)	-0.215* (0.129)
Neighbourhood Theft		-0.036 (0.030)		0.034 (0.035)	0.043 (0.047)	0.032 (0.038)
Attrition		-0.187* (0.098)		0.015 (0.132)	-0.117 (0.194)	0.088 (0.152)
Constant	18.588*** (0.128)	21.169*** (0.326)				
Year	YES	YES	YES	YES	YES	YES
Other Government Support	NO	YES	NO	YES	YES	YES
Child Age Dummy	NO	YES	NO	YES	YES	YES
Province	NO	YES	NO	YES	YES	YES
Region	NO	YES	NO	YES	YES	YES
Observations	28,773	28,773	28,773	28,773	9,147	19,626
Individuals			10,925	10,925	3,723	7,202
R-squared	0.015	0.065	0.019	0.025	0.026	0.029

The outcome variable is CES-D (0-30) the measure for depression; PSU clustered standard errors are in parenthesis; *** p<0.01, ** p<0.05, * p<0.1.

Table 6 Robustness tests: Sample estimations: First stage

	(1) Study Sample	(2) Baseline	(3) Full Sample	(4) Full Balanced	(5) Study Balanced
CSG eligible child	0.644*** (0.016)	0.596*** (0.014)	0.544*** (0.014)	0.546*** (0.016)	0.636*** (0.018)
Age	0.011** (0.005)	0.016*** (0.004)	0.013*** (0.004)	0.017*** (0.004)	0.014** (0.007)
Age Squared	-0.000* (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000** (0.000)	-0.000 (0.000)
Age under 19	0.012 (0.011)	0.031*** (0.011)	0.014 (0.009)	0.015 (0.015)	0.011 (0.018)
Economic dec. maker	-0.001 (0.005)	-0.000 (0.005)	-0.001 (0.004)	-0.001 (0.005)	-0.003 (0.007)
Household Size	0.010*** (0.003)	0.012*** (0.003)	0.012*** (0.003)	0.013*** (0.003)	0.010*** (0.003)
Negative Event	0.005 (0.009)	0.002 (0.009)	0.010 (0.008)	0.006 (0.009)	0.006 (0.010)
Neighbourhood Theft	-0.001 (0.002)	0.000 (0.002)	0.001 (0.002)	-0.000 (0.002)	-0.004 (0.003)
Attrition	-0.005 (0.009)	0.002 (0.009)	-0.003 (0.006)		
Year	YES	YES	YES	YES	YES
Other Gov. Support	YES	YES	YES	YES	YES
Child Age Dummy	YES	YES	YES	YES	YES
Province	YES	YES	YES	YES	YES
Region	YES	YES	YES	YES	YES
Observations	28,773	29,614	48,872	26,553	16,573
Individuals	10,925	9,567	17,164	7,717	5,540
R-squared	0.305	0.345	0.326	0.322	0.303

The outcome variable is the binary indicating if the individual lives in a household that received the CSG or not; (1) is the sample applied throughout this study, with restricting the sample to per capita income \leq R800, (2) is the using individuals recorded in the baseline according to the selection in (1) throughout the waves, (3) is the full NIDS sample, (4) is the full balanced NIDS sample, (5) is the balanced sample (1). We control for the full set of covariates and where indicated for year, other government support programmes, child age, province and region effects; PSU clustered standard errors are in parenthesis; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7 Robustness tests: Sample estimations: Second stage

	(1) Study Sample	(2) Baseline	(3) Full Sample	(4) Full Balanced	(5) Study Balanced
Household CSG	0.822*** (0.279)	0.673*** (0.234)	0.502** (0.214)	0.861*** (0.255)	1.147*** (0.300)
Age	0.133* (0.080)	-0.001 (0.077)	0.083 (0.070)	0.003 (0.079)	0.002 (0.098)
Age Squared	0.001* (0.000)	0.001** (0.000)	0.000 (0.000)	0.001* (0.000)	0.001** (0.000)
Age under 19	0.380** (0.169)	0.681*** (0.173)	0.464*** (0.135)	0.691*** (0.199)	0.445* (0.234)
Economic dec.	0.041 (0.082)	0.103 (0.075)	0.000 (0.059)	-0.005 (0.074)	0.033 (0.097)
Household Size	0.042 (0.037)	0.056* (0.032)	0.054* (0.030)	0.059* (0.032)	0.066* (0.036)
Negative Event	-0.050 (0.115)	-0.213* (0.109)	-0.189* (0.099)	-0.349*** (0.112)	-0.277** (0.123)
Neighbour. Theft	0.034 (0.035)	-0.005 (0.031)	0.021 (0.027)	0.001 (0.031)	0.006 (0.041)
Attrition	0.015 (0.132)	-0.118 (0.128)	-0.100 (0.098)		
Year	YES	YES	YES	YES	YES
Other Gov. Support	YES	YES	YES	YES	YES
Child Age Dummy	YES	YES	YES	YES	YES
Province	YES	YES	YES	YES	YES
Region	YES	YES	YES	YES	YES
Observations	28,773	29,614	48,872	26,553	16,573
Individuals	10,925	9,567	17,164	7,717	5,540
R-squared	0.025	0.021	0.015	0.019	0.028

The outcome variable is CES-D (0-30) the measure for depression;(1) is the sample applied throughout this study, with restricting the sample to per capita income \leq R800, (2) is the using individuals recorded in the baseline according to the selection in (1) throughout the waves, (3) is the full NIDS sample, (4) is the full balanced NIDS sample, (5) is the balanced sample (1). We control for the full set of covariates and where indicated for year, other government support programmes, child age, province and region effects; PSU clustered standard errors are in parenthesis; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8 Robustness test: Sample estimations: Placebo tests and non-recipient test first stage

	(1) First Stage: HH without immediate CSG Recipient	(2) First Stage: Placebo test wave 1-3	(3) First Stage: Placebo test all waves
CSG eligible child	0.534*** (0.019)	0.045 (0.065)	0.135*** (0.023)
Male		-0.088*** (0.030)	0.007 (0.009)
Age	-0.005 (0.007)	-0.008 (0.005)	0.002 (0.002)
Age Squared	0.000** (0.000)	0.000 (0.000)	-0.000 (0.000)
Age under 19	0.037** (0.015)	-0.057 (0.052)	-0.001 (0.017)
Economic decision maker	-0.021** (0.009)	0.011 (0.026)	-0.009 (0.009)
Household Size	0.025*** (0.005)	0.057*** (0.015)	0.013*** (0.005)
Negative Event	0.004 (0.012)	-0.013 (0.032)	0.019 (0.013)
Neighbourhood Theft	-0.002 (0.003)	-0.002 (0.010)	-0.003 (0.004)
Attrition	-0.008 (0.011)		
Constant		0.515*** (0.167)	-0.078 (0.053)
Year	YES	YES	YES
Other Government Support	YES	YES	YES
Child Age Dummy	YES	YES	YES
Province	YES	YES	YES
Region	YES	YES	YES
Observations	16,332	1,749	2,122
Individuals	6,808		
R-squared	0.315	0.144	0.486

The outcome variable in (1) is the variable indicating if the individual lives in a CSG-receiving household", in (2) and (3) is the binary variable indicating if the individual lives in a household which receives the CSG only in the last wave; Model (1) is the first stage instrumental variable estimation of the study sample without the receiving care taker of the grant in the household, (2) is the pooled cross-sectional instrumental variable first stage estimation of the placebo test comparing individuals living in never-receiving households with individuals that live in a household which receives the CSG only in the last wave, a balanced panel over the first three waves is used for the estimation, (3) is taking all four waves for the instrumental variable pooled-cross sectional analysis into account but the comparison remains. We control for the full set of covariates and where indicated for year, other government support programmes, child age, province and region effects; PSU clustered standard errors are in parenthesis; *** p<0.01, ** p<0.05, * p<0.1

Table 9 Robustness test: Sample estimations: Placebo tests and non-recipient test including second stage

	(1) FE 2SLS: without immediate CSG Recipient	(2) Placebo test wave 1-3	(3) 2SLS: Placebo test wave 1-3	(4) 2SLS: Placebo test all waves
Last Wave CSG		0.104 (0.266)	22.370 (31.447)	
Household CSG	1.220*** (0.388)			7.016*** (2.485)
Male		0.482** (0.196)	2.480 (2.877)	0.620*** (0.195)
Age	0.025 (0.109)	-0.082** (0.034)	0.086 (0.270)	-0.086*** (0.034)
Age Squared	0.001 (0.001)	0.001** (0.000)	-0.001 (0.002)	0.001** (0.000)
Age under 19	0.256 (0.220)	0.406 (0.535)	1.736 (2.307)	0.642 (0.525)
Economic decision maker	0.044 (0.122)	-0.455** (0.230)	-0.698 (0.700)	-0.322 (0.206)
Household Size	-0.041 (0.051)	0.035 (0.097)	-1.246 (1.868)	-0.002 (0.103)
Negative Event	0.089 (0.139)	-0.241 (0.304)	0.043 (0.931)	-0.507* (0.294)
Neighbourhood Theft	0.055 (0.041)	-0.131 (0.080)	-0.080 (0.254)	-0.098 (0.078)
Attrition	0.142 (0.156)			
Constant		22.142*** (1.002)	10.621 (16.709)	22.136*** (1.029)
Year	YES	YES	YES	YES
Other Government Support	YES	YES	YES	YES
Child Age Dummy	YES	YES	YES	YES
Province	YES	YES	YES	YES
Region	YES	YES	YES	YES
Observations	16,332	1,749	1,749	2,122
Individuals	6,808			
R-squared	0.019	0.108	-4.248	0.025

The outcome variable is CES-D (0-30) the measure for depression; (1) is the instrumental variable estimation of the study sample without the receiving care taker of the grant in the household, (2) is the pooled cross-sectional estimation of the placebo test comparing individuals living in never-receiving households with individuals that live in a household which receives the CSG only in the last wave, a balanced panel over the first three waves is used for the estimation, (3) is the same as in (2) but using the cross-sectional pooled instrumental variable “eligible child for CSG in household” for the placebo test, (4) is taking all four waves for the instrumental variable pooled-cross sectional analysis into account but the comparison remains. We control for the full set of covariates and where indicated for year, other government support programmes, child age, province and region effects; PSU clustered standard errors are in parenthesis; *** p<0.01, ** p<0.05, * p<0.1.

Table 10 Fixed effect estimation of CES-D on child eligibility with individuals living in financially non-eligible households

	(1) FE with covariates
CSG eligible child	0.204 (0.257)
Age	0.093 (0.152)
Age Squared	-0.000 (0.001)
Age under 19	0.787** (0.334)
Economic decision maker	-0.021 (0.125)
Household Size	0.011 (0.084)
Negative Event	-0.502* (0.274)
Neighbourhood Theft	0.043 (0.044)
Attrition	-0.243 (0.178)
Constant	17.371*** (5.160)
Year	YES
Other Government Support	YES
Child Age Dummy	YES
Province	YES
Region	YES
Observations	21,720
Individuals	13,982
R-squared	0.016

The outcome variable is CES-D (0-30) the measure for depression.

We control for the full set of covariates; PSU clustered standard

errors are in parenthesis; *** p<0.01, ** p<0.05, * p<0.1.

APPENDIX: *The effect of cash transfers on mental health – New Evidence from South Africa*

We present in section A1 the descriptive analysis of individuals living in cash transfer receiving households with individuals living in cash transfer non-receiving households and in A2 a descriptive analysis on sample attrition and transition.

A1 Comparison of individuals by CSG status

Table A1 compares individuals living in recipient and non-recipient households. Individuals living in CSG recipient households have on average a slightly higher mean CES-D score (19.8 vs. 19.4) than individuals living in non-recipient households. About 42% of individuals from a non-recipient household live with a CSG eligible child, whereas 99.4% of individuals from a CSG receiving household live with a CSG eligible child. The composition of households varies by CSG status. In non-recipient households, 40% are male (24% in a receiving household), with average age of about 42 years (39 years in a receiving household). 57% of individuals in CSG-non-recipient household are involved in economic decision making compared to 49% in CSG-receiving households. The average size of recipient households is much larger (6 versus 3.5 individuals). The negative shock of a death in the household occurred to about 13% of individuals from non-recipient households compared to about 14% from receiving households. We observe a fairly similar share of participation in the other social grant programmes between CSG recipient and non-recipient households.

A2 Attrition and transition

Table A2 describes attrition and transition between the waves. Transition is defined here as moving in or out of the sample study due to increase or reduction in income and falling below or stepping above the R800 income threshold. Between 2008 and 2010, 1,135 of 6,801 individuals moved above the income threshold with 593 individuals moving below the threshold. Transition increases in both directions over the years involving 2,355 of 7,818 individuals moving above the threshold between 2012 and 2014 and 1,011 moving below the threshold. Attrition is defined here as temporarily or permanently leaving the survey between the waves. 4,215 individuals left the study between 2008 and 2010, 4,715 between 2010 and 2012 and 2,678 between 2012 and 2014. Attrition amongst poor individuals amounts to 2,769 individuals between 2008 and 2010, 3,271 between 2010 and 2012, and 2,678 from 2012 to 2014.

Mental health outcomes are similar for individuals moving out of the lower income

bracket and individuals moving into the lower income bracket (19.69 vs. 19.65 over 2008-2010, 20.42 vs. 20.17 over 2010-2012, 20.63 vs. 20.88 over 2012-2014). The average CES-D amongst the individuals leaving the survey between the waves is fairly similar to the average of the survey samples for the waves. Individuals leaving between 2008 and 2010 had a mean CES-D score of 19.44 vs. 18.99 for the study sample in 2008, individuals leaving between 2010 and 2012 had a mean CES-D score of 20.319 vs. 20.07 of observations in 2010 (table A3), and 20.633 versus 20.12 in 2012 (table A3). The mean scores of CES-D amongst low-income individuals leaving the survey between waves are fairly similar to the sample by each wave.

Table A6**Summary statistics comparison of individuals in household receiving and non-receiving CSG**

	CSG Non-Receiving Household (n=3,855)	CSG-Receiving Household (n=9,682)	t-test of difference
CES-D	19.373 (4.042)	19.887 (3.705)	-7.099
Household with CSG eligible child	0.426	0.994	-109.816
Male	0.393	0.236	26.160
Age (years)	41.867 (14.749)	39.125 (12.273)	11.055
Age under 19	0.090	0.105	-3.950
Economic decision maker	0.569	0.490	11.413
Size of the household	3.513 (2.013)	6.084 (2.897)	-50.485
Death in household	0.130	0.144	-2.027
Household Old Age Pension	0.307	0.331	-2.756
Household DG	0.097	0.107	-1.745
Household FCG	0.048	0.043	1.215
Household CDG	0.014	0.012	1.127
Neighbourhood Theft	2.035 (1.457)	2.066 (1.454)	-1.111
Region	1.44 (0.795)	1.337 (0.734)	7.572
Attrition	0.114	0.090	5.136

Note: Descriptive statistics are on the sample of the estimated models over all years. n indicates the number of households. Variable means (standard deviations). T-test are testing for $H_0: \text{diff} = 0$ in mean.

Table A7**Number of compliers, always takers, never takers of the CSG on the household level by NIDS waves**

	2008	2010	2012	2014
Compliers	5,546	6,828	6,943	4,913
Always takers	0	41	24	22
Never takers	1,189	918	748	340
Share of Always takers with compliers	0.000	0.006	0.003	0.005
Share of Never takers with compliers	0.214	0.134	0.107	0.069

*Defiers are ruled out by the monotonicity assumption of the LATE saying that individuals have a clear preference over their choice to participate in the grant scheme.

Table A3 Summary statistics transition and attrition between NIDS waves

	2008-2010	2010-2012	2012-2014
$t + 1 > R800 \geq t$	1,135	1,710	2,355
$t + 1 \leq R800 < t$	593	604	1,011
Attrition	4,215	4,715	4,197
Attrition $R \leq 800$	2,769	3,271	2,678
CES-D	19.692 (0.138)	20.423 (0.102)	20.634 (0.090)
$t + 1 > R800 \geq t$			
CES	19.657 (0.196)	20.178 (0.181)	20.889 (0.141)
$t + 1 \leq R800 < t$			
CES-D Attrition	19.44 (0.071)	20.319 (0.060)	20.633 (0.072)
CES Attrition $R \leq 800$	18.902 (0.085)	20.115 (0.072)	20.428 (0.086)

Mean values reported for CES-D. Standard deviations in parenthesis.