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Is the impact of the South African child support grant on childhood stunting robust? An instrumental variable evaluation

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ABSTRACT

The Child Support Grant (CSG) is part of the South African Social Assistance Programme, which costs the country approximately 1.3% of GDP annually. Given the scale of this programme, it is important to assess whether it has had an impact on the long-term health outcomes of children. Extant literature on the impact of CSG on a child's long run nutritional status as measured by the height-for-age relies on the optimistic assumption that estimation controls for all relevant variables (i.e. the ignorability assumption). Further existing analysis are based on older datasets (i.e. older waves of the National Income Dynamic Study (NIDS)). We examine the robustness of the results to bias due to unobserved variables, using more recent data (the 2014/2015 and 2017 NIDS). Using the possession of the necessary government-issued documentation to access the grant as an instrumental variable (IV) we find that existing results are robust to the IV framework. Further, acknowledging the limitation of the instrumental variable, we show that the result is robust to violation of various assumptions underlying the IV approach. We argue that while the CSG remains a crucial contributor to early childhood development in South Africa, there is a need to critically examine its impact on nutritional status given the importance of this variable for intergenerational transmission of poverty.

1. Introduction

Social assistance programmes are increasingly being recognised as a tool to alleviate poverty and to improve the health outcomes among vulnerable sub-groups such as children, single mothers, the disabled and the elderly. South Africa has a social assistance programme which consists of several tax-financed, non-contributory and conditional cash transfers including the Child Support Grant (CSG), Older Persons Grant, Disability Grant, War Veterans' Grant, Foster Care Grant, Care Dependency Grant, Grant-in-aid and the recent Covid-19 Social Relief Distress (SRD) grant (Moore and Seekings, 2019; Köhler and Bhorat, 2020). In terms of cost, CSG is the largest of these welfare schemes (Oyenubi and Kollamparambil, 2022).

The South African child support grant (CSG) in its current form was first rolled out in 1998, with the age eligibility criteria gradually increasing over time. The grant is child-focused as opposed to a family-based benefit, allocated to each child aged 18 years and younger, paid to the primary caregiver.[1] The South African social assistance programme is largely pro-poor (Van der Berg, 2014), and prior to the COVID-pandemic, slightly more than 50 % of South African children were receiving some form of a social grant (South African Social Security Agency (SASSA), 2019). The CSG programme cost South Africa R60.6 billion in the 2018/2019 financial year (South African Social Security Agency (SASSA), 2019), or roughly 1.3 % of the South African Gross Domestic Product (UNICEF, 2019).

The goal of the Child Support Grant is to assist with the cost of living of children from socioeconomically disadvantaged backgrounds. Given the scale of the South African social protection system, it is important to assess whether it has had an impact on the long-term health outcomes of children. Stunting refers to a child's impaired height for age, which occurs due to poor nutrition or repeated illness and infection. Linear growth delay, as stunting is often called, is an indicator of long-term exposure to these poor conditions (Said-Mohamed et al., 2015). The South African Demographics and Health Survey estimated that 27.4 % of children under the age of five were stunted in 2016 (National Department of Health (NDoH) et al., 2019). Although South Africa is classified as an upper-middle income country, the levels of stunting is high given this level of economic development (Said-Mohamed et al., 2015).

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[1] Primary caregiver is defined as the person who is responsible for the child's daily need and does it without payment.

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Seminal health economics papers have made several arguments for investing in health capital, including that it results in positive economic returns such as increased labour productivity and lifetime earnings (Strauss, 1986, Strauss and Thomas, 1998). Nutrition is a key part of this health capital. Stunting has been linked to long-term consequences in South Africa, including compromised cognitive functioning (Casale et al., 2018) and schooling outcomes (Yamauchi, 2008, Casale, 2016).

Basic financial support such as the CSG may affect stunting through a myriad of avenues. This includes the reduction in poverty (Van Der Berg, 2014), which in turn results in increased access to nutritious food, education, quality healthcare and improved maternal decision-making (Patel et al., 2015). Improved schooling among mothers is correlated to better feeding practices, improved diets for their children, a higher likelihood of child vaccinations, and a healthier antenatal environment (Casale et al., 2018; Makoka, 2013). These factors all contribute to reduced stunting among children. It is important to note that if the CSG has had the intended positive impact on child nutrition then one would have expected the rate of stunting to be lower in South Africa.[2] The stubbornly high prevalence rate of stunting suggests that the link between CSG and access to nutritious food require further examination given that a large proportion of children (63 %) under the age of 17 are beneficiaries.[3] This suggests that there may be heterogeneous effects where there are complimentary factors that maximize the effect of receiving the grant. Policy that enhances complementary factors (like caregiver’s education) can therefore increase the efficiency of the programme.

Papers studying the impact of the South African CSG on stunting have reported mixed results, (Oyenubi, 2020; Oyenubi, 2021; Aguero et al., 2006; Coetzee, 2013; Zembe-Mkabile et al., 2016). Aguero and coauthors (2006), studying the impact of the CSG in the South African province of Kwazulu-Natal during the first years of roll-out, found that children receiving the grant for at least the first 50 % of their first 36 months of life had a significant improvement in their height-for-age scores. Coetzee (2013), focusing on the entire South African population 10 years after the roll-out of the CSG, finds a positive but small effect on child nutrition. Oyenubi (2021) shows that the CSG was predominantly to the benefit of girl children who did not experience low birth weight, while the CSG had little effect on boy children and those with low birth weight. In a cross-sectional analysis of primary data collected in three areas of South Africa, Zembe-Mkabile et al. (2016) did not find that the CSG grant was correlated to lower stunting rates. Given the mixed results an update on the impact of CSG on height-for-age in South Africa is needed. Further all the studies cited above are based on data collected before 2014. This is important since between 2014 and 2018 the take-up rate of CSG has increased by about 10 %.[4]

Further, a key limitation of existing studies measuring the impact of the CSG on height-for-age has been their reliance on the assumption that all confounders are accounted for by the observed controls (i.e. the Conditional Independence Assumption (CIA)). An assumption which is unlikely to be met in practice. To address this limitation, we estimate the causal impact of the CSG on stunting using the instrumental variable approach. Unlike methods that rely on the CIA, the IV approach provides a causal inference that is robust to unobserved attributes. Following a recent paper (Oyenubi and Kollamparambil, 2022), we use documentation required for applying for a CSG as a source of an exogeneous variation in our IV framework. This documentation is the South African Identity Card (ID).[5] This document is necessary for processing the CSG application. Our analysis is performed using the most recent nationally representative data set which contains anthropometric measures (i.e., wave 4 (collected in 2014/2015) and wave 5 (collected in 2017) of the National Income Dynamic Study (NIDS)) which to the best of our knowledge is yet to be used for analysing the impact of the grant.

While the IV approach is robust to unobserved factors it is also limited in that it relies on certain assumptions (namely monotonicity, relevance, and instrument validity). Monotonicity assumption require that all individuals respond to the instrument in the same direction (Olivo-Villabrille, 2021). This means that there are no defier subjects, i.e., subjects who will take control when the instrument suggests they should to take treatment (this assumption rules out the existence of respondents that are not benefiting from the CSG even though they are qualified and have the South African ID) or vice versa. However, arguments about variation in caregiver motivation (in applying for the grant) will suggests that such defiers are probable, it is known that the presence of such defiers in the sample can biased the result (De Chaisemartin, 2017). Hence the need to check robustness of results to this assumption. Further, while finding instrumental variable(s) that are correlated with the endogenous variable (relevance of instrument assumption) is relatively easy, motivating that the instrument is uncorrelated with the outcome except through the endogenous variable (validity of instrument) is much more difficult (Clarke and Matta, 2018). The implication of this assumption is that posession of ID is uncorrelated with the health of children except through its effect on CSG receipt. Similar to the argument on violation of the monotonicity assumption, caregivers with lower motivation may also be more likely to care for children with pooorer health, thereby inducing correlation between the instrument and the outcome and invalidating the assumption. To address this concern we use an approach that allows us to estimate a confidence interval for the effect estimate even when the validity assumption fails (Clarke and Matta, 2018). Such confidence interval is informative about the size and direction of the effect estimate even if the instrument validy assumption does not hold.

Further, to examine the influence of unobserved attributes, we re-estimate the effect under the CIA assumption (using the entropy balancing method (Hainmueller, 2012)), and use the Oster bounds method (Oster, 2019) to check the robustness of the estimate to omitted variable bias. This approach use selection on observable characteristics to provide information on selection along unobserved factors (Altonji et al., 2005). This approach will reveal how much stronger selection on unobserved attributes must be relative to selection on observables to nulify the result.

2. Methodology

2.1. Data and variables

NIDS is a nationally representative household survey which predominantly collects information on poverty, income, and well-being of South Africans. NIDS does contain a specific and detailed module pertaining to health outcomes, including the anthropometric measurements of children and adults. These anthropometric measurements were used to assess whether children were stunted. The data was collected by the South African Labour and Development Research Unit based at the

[2] Both the prevalence and number of stunted children in South Africa have increased since 2008. While the prevalence in South Africa is lower than other Southern African countries it is still high compared to international benchmarks see https://www.unicef.org/southafrica/sites/unicef.org.southafrica/files/2020–07/ZAF-Nutrition-brief-2020.pdf.

[3] https://www.statssa.gov.za/?p=14038#:~:text=More%20than%20two%2Dthirds%20(68,declining%20over%20the%20past%20decade.

[4] https://www.statista.com/statistics/1261146/share-of-children-who-received-child-support-grant-by-population-group-in-south-africa/. Reports show that this increased further during the COVID-19 pandemic see https://www.unicef.org/southafrica/media/7971/file/%20ZAF-update-study-exclusion-error-children-eligible-receive-child-support-grant-June-2023.pdf.

[5] Reg. 11(1) of the Regulations Relating to the Application for and Payment of Social Assistance and the Requirements or Conditions in Respect of Eligibility for Social Assistance, Published under Government Notice R898 in Government Gazette 31,356 of 22 Aug. 2008.

University of Cape Town, South Africa (Brophy et al., 2018).

The data followed a two-stage sampling with stratification at the district council level. A total of 14,993 children (aged 14 and younger) were interviewed in wave 5 (Brophy et al., 2018), although our sample is limited to children aged five years and younger (who also qualify to receive the grant, as discussed in a later paragraph). The age limitation is based on the official definition of child stunting as used by stakeholder organisations (Unicef, 2013), and convention followed by other studies (Akombi et al., 2017; Grantham-McGregor et al., 2007). A child is classified as stunted when their height-for-age is less than two standard deviations below the median of the healthy reference population, as established by the WHO Child Growth Standards. We refer to this standard deviation as the HAZ, or height-for-age Z-score (World Health Organization, 2006).

To limit measurement error, NIDS took height measurements twice and then a third time if the first two measurements differ by more than a centimetre. Height-for-age Z-score was then calculated using the WHO international child growth standards as the reference population (Brophy et al., 2018). Child Support Grant recipients are identified using the following questions “Does someone receive a social grant for the child?” and “What type of grant?”. A “yes” to the first question, and “Child Support Grant” for the second question means that the child is a beneficiary.

Our estimation sample contains children that satisfy the administrative requirement for receiving the grant. This requirement in 2017 require that the child is age-eligible and has a caregiver that satisfies the means test. Although age eligibility is under 18 years of age, our sample is restricted to those that are five years or younger. The means test specifies a threshold amount for caregiver income and caregivers that fall below this threshold qualify to receive the grant. The threshold in 2017 requires that if the caregiver is unmarried, they have an annual income that is below ten times the annual grant amount prevailing at the time of their application. If married, the combined income of the caregiver and the spouse should be below 20 times the annual grant amount (South African Social Security Agency (SASSA), 2019).[6] Therefore, the comparison group in our sample is made up of children who satisfy these administrative requirements but are not yet benefiting from the grant. Lastly, we exclude households where some children receive the CSG, but others do not. While this imply that control children are those in the worst possible situation (i.e. qualify for CSG because of their socioeconomic status but not benefiting from it), we deem this restriction necessary to mitigate spillover effects. We note that this means that our estimate is likely to be the upper bound of the effect of CSG on stunting.

We control for a range of covariates, including primary caregiver’s employment status, marital status, education, age and their relationship to the child. We also control for child’s gender, race and age, whether they were underweight at birth, and whether the child has been ill for at least 3 days in the last month. Household characteristics, such as their access to electricity, a flush toilet, rural–urban residence, and the total household expenditure per household resident, gender of household head, description of the household physical structure (dummy for apartment building, dilapidated and informal dwelling) and wave dummy are also included in the analysis.

2.2. Identification and empirical strategy

Simply comparing stunting between children who received the CSG and those who did not receive the CSG is likely to deliver biased results. There are omitted variables which are likely to be correlated with both CSG and stunting. To see this, consider that socio-economic, environmental and nutritional factors play distinct, but associated roles in determining the health outcomes of children (Chopra, 2003). Receipt of the CSG can be regarded as one such a socio-economic determinant of child health. However, there may be unmeasured and unmeasurable variables that are correlated with grant receipt and child health. For example, Oyenubi (2021) argues that whether a child is related to the primary caregiver matters when it comes to how quickly a child is enrolled for the CSG, this is related to caregiver motivation which extant literature identify as an unobserved factor. Furthermore, Chopra (2003) found that having a migrant father is related to a child’s height-for-age. The implication is that there are complex interactions within the household structure, registering for a CSG and health outcomes that may not be well captured by the NIDS dataset.

Existing literature on this topic argue that caregiver motivation is an important unobserved factor that can bias the impact estimate (Coetzee, 2013, Oyenubi, 2020). To account for this, caregiver motivation is estimated from data as the difference between observed delay and expected delay. The idea is that the difference between observed and expected delay is a useful proxy for motivation, or lack thereof, since it captures the eagerness of the caregiver to apply for the CSG. Expected delay is based on an OLS model that regress observed delay on a set of characteristics that are assumed to affect delay (geo location, child’s age and relationship between the child and the primary caregiver) (Oyenubi, 2020). However, this strategy ignores how changes in socioeconomic status or changes in eligibility rules can affect meeting the administrative requirements to qualify for the grant. For example, given the high level of poverty and inequality in South Africa, a child may be born at a time when the caregiver (financially) does not qualify for the CSG, if there is a change in socioeconomic status over time the child may later become eligible. However, the strategy stated above will misconstrue delay on the part of the caregiver as a lower level of motivation.

Instead of the approach that relies on the CIA, we follow the approach of Oyenubi and Kollamparambil (2022) who use possession a key document required to apply for the CSG as an instrument for CSG receipt to address the endogeneity problem. The main obstacle to implementing the IV approach is finding a good instrument. A good instrument needs to be correlated to the treatment (CSG receipt), but not the outcome variable (Stunting).

In order to apply for the CSG, the caregiver needs to present their bar-coded South African Identity Card (ID), and the child’s clinic card (the latter is not a valid instrument since it is correlated with health). Ownership of these documents are necessary to process the grant application, and without them, application can be delayed or denied. Furthermore, the process of securing this documentation from various government agencies may delay the application process, further delaying the child access to the grant in earlier stages of the child’s life where access to this resource is more important. Possession of ID is self-reported by the respondents. Hindrance/delay in accessing the CSG due to lack of documentation is well documented in the literature (Delany et al, 2008).

Possession of ID is relevant because of its correlation with grant receipt (this can be empirically assessed with the weak identification test), the instrument is argued to be exogeneous to individual caregivers (or exogeneous conditional on observed covariates) since procuring these documents depends on the efficiency of government bureaucratic process (this assumption is often assessed using the overidentifying restriction test (Van Kippersluis and Rietveld, 2018), but that will not be possible in our application since we have only one instrument). Lastly, as argued by Oyenubi & Kollamparambil (2022), the required documents satisfy the exclusion restriction, namely the possession of an ID by the caregiver does not directly affect the stunting status of children except through the CSG. In other words, there is no reason why possession of an ID should influence the height-for-age of children under the care of the caregiver since ID is not a requirement for other social services like

[6] Since the grant amount changed on 1 April 2017, there are two possible threshold amounts for our data. Interviews for wave 5 of the NIDS survey were conducted between February and December 2017 (Brophy et al., 2018: 28). For those in the NIDS survey interviewed before April 2017, the threshold amount is R43200. For those in the NIDS survey interviewed after April 2017, the threshold amount is R45600.

Table 1
Descriptive statistics of dependent variable, instruments and covariates, disaggregated by CSG receipt status.

		CSG recipient				CSG non-recipient			
		Mean	Standard deviation (if continuous variable)	Minimum	Maximum	Mean	Standard deviation (if continuous variable)	Minimum	Maximum
Grant recipient		0.25		0	1	0.23		0	1
Instruments	Primary caregiver has ID	0.94		0	1	0.81		0	1
Primary caregiver characteristics	Married	0.29		0	1	0.27		0	1
	Education: Degree	0		0	1	0.02		0	1
	Employed	0.3		0	1	0.05		0	1
	Age	33.12	12.24	16	91	39.18	17.38	16	84
	Primary Caregiver is child's Mother or Father	0.8		0	1	0.62		0	1
Child characteristics	Male gender	0.48		0	1	0.55		0	1
	Underweight	0.09		0	1	0.06		0	1
	Black	0.89		0	1	0.88		0	1
	Child has had a Serious Illness/Disability	0.03		0	1	0.04		0	1
	Child has been ill for at least 3 days in the last month	0.12		0	1	0.08		0	1
	Age in years	2.83	1.29	0.1	5	2.57	1.34	0.49	4.99
Household Characteristics	Flush toilet	0.2		0	1	0.24		0	1
	Rural residence	0.59		0	1	0.56		0	1
	Electricity	0.84		0	1	0.86		0	1
	Male household head	0.3		0	1	0.26		0	1
	Dwelling type: apartment	0.01		0	1	0.03		0	1
	Dwelling quality: dilapidated	0.25		0	1	0.22		0	1
	Dwelling type: informal dwelling	0.16		0	1	0.11		0	1
	Household per capita expenditure	693.57	989.23	48.25	34596.5	920.36	1057.33	117.74	8598.33
Wave 4		0.84		0	1	0.86		0	1
Wave 5		0.3		0	1	0.26		0	1
Observations		5148				449			

SD=Standard deviation; Min = Minimum; Max = Maximum.

healthcare. We consider a model of the following form.

$$S_i = \alpha + \beta CSG_i + \beta x_i + \varepsilon_i$$

where S_i is the height-for-age of child i, CSG is the dummy variable that is 1 when the child is a recipient and 0 otherwise and x is a vector of covariates included in the analysis (see Table 1 for details). As noted earlier, CSG receipt status may be endogenous because of unmeasured covariates that are correlated with receipt status and the outcome. Therefore, we use the IV approach where possession of an ID is used as instrument. The first stage of the IV regression is given by:

$$CSG_i = \alpha + \beta Instrument_i + \beta x_i + \vartheta_i$$

Inference relies on bootstrapped standard errors and are clustered at the household level to account for the inter household correlation.

We conducted robustness checks to examine the validity of the IV assumptions. First, we examine the monotonicity assumption following De Chaisemartin (2017). This requires estimating the worst-case bounds for the treatment effect of "comvivors" (see the appendix and section 3.2 for details) and establishing that the estimated treatment effect lies within this bounds. Second, we examine the instrument validity assumption following Nevo and Rosen (2012). Under this approach, analytic bounds for the parameter of interest can be derived under certain assumptions: (i) the instrument has the same direction of correlation with the omitted error term as the endogenous variable (ii) the instrument is less endogenous than the endogenous variable. Under the assumption that caregiver motivation is the omitted variable, it is safe to assume that both the endogenous treatment (CSG receipt) and the instrument (possession of ID) are positively correlated with the omitted variable. The second assumption requires that the relationship between CSG receipt and caregiver motivation is stronger than the relationship between possession of ID and caregiver motivation. This is a reasonable assumption given that caregivers who are receiving the grant are arguably more motivated to improve their child's health than those who have an ID but are not yet receiving the grant.

Third, we estimate the effect under the CIA using the entropy balancing method (Hainmueller, 2012; Oyenubi, 2021). This check serves two purposes, first the result of this analysis can be compared with existing results that are based on similar assumption but use earlier waves of the same data. Further, since this approach is based on a weighted regression, we can use the Oster (2019) approach to examine the influence of unobserved factors on the effect estimate i.e. how sensitive is the result obtained under the CIA assumption to unobserved factors.

3. Results

3.1. Main result

The descriptive statistics of the variables used in the analysis are reported in Table 1. The descriptive statistics are disaggregated by CSG receipt. The results show that in the sample, 25 % of children who received the CSG grants were stunted, while 23 % of those who did not

Table 2
Instrumental Variable results.

		First	Second
Grant recipient			−0.31**
			(0.16)
Primary caregiver characteristics	Married	0.01	0.01
		(0.02)	(0.01)
	Education: Degree	−0.18*	−0.18**
		(0.11)	(0.09)
	Employed	0.09***	0.03
		(0.01)	(0.02)
	Age	−0.00**	0
		(0)	(0)
	Primary Caregiver is child's Mother or Father	0.04**	0.03
		(0.02)	(0.02)
Child characteristics	Male gender	−0.03**	0.04***
		(0.01)	(0.01)
	Underweight	0.03*	0.19***
		(0.02)	(0.03)
	Black	0.02	−0.01
		(0.02)	(0.02)
	Child has had a Serious Illness/ Disability	−0.04	0.03
		(0.04)	(0.04)
	Child has been ill for at least 3 days in the last month	0.02	0.02
		(0.02)	(0.02)
	Age in years	0.01**	−0.03***
		(0)	(0.01)
Household Characteristics	Flush toilet	−0.01	−0.03
		(0.02)	(0.02)
	Rural residence	0	0.01
		(0.01)	(0.02)
	Electricity	−0.03**	0
		(0.01)	(0.02)
	Male household head	0.02	−0.01
		(0.01)	(0.01)
	Dwelling type: apartment	−0.09	0.01
		(0.06)	(0.06)
	Dwelling quality: dilapidated	−0.01	0.04***
		(0.01)	(0.01)
	Dwelling type: informal dwelling	0.02*	0.02
		(0.01)	(0.02)
	Household per capita expenditure	−0.00***	−0.00***
		(0)	(0)
Wave 4		−0.02	0.01
		(0.01)	(0.01)
Primary caregiver has ID		0.14***	0
		(0.03)	(0)
Observations		5,583	5,587
R-squared			
Under identification test (LM statistic)			37.7
Weak identification test (Wald F statistic)			43
Endogeneity test			4.835
Endogeneity p-value			0.0279

Robust bootstrapped (99) standard errors in parentheses.
Estimation is clustered at household level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

receive the grant were stunted (a larger proportion of treatment children in the treatment group is likely because this is a bivariate analysis that does not control for other factors). The result of the IV linear probability model is reported in Table 2, with different tests to check the validity of the IV approach reported in the last 3 rows. The LM under-identification test is significant showing that the IV is relevant. The weak identification test suggest that the instruments are not weak (also the coefficients of ID in the first stage regression are large and statistically significant). Lastly, the null hypothesis of the endogeneity test is rejected suggesting that treatment status cannot be treated as an exogenous variable in our model.

Our main results show that CSG receipt reduces the rate of stunting in the population of beneficiaries, stunting is 31 % lower compared to the population of qualified but non-benefiting children (significant at the 5 % level). This is consistent with the results that rely on the CIA assumption (Aguero et al., 2006; Coetzee, 2013; Oyenubi, 2020; Oyenubi, 2021). However, since the validity of the instrument can be questioned, we proceed to conduct robustness checks.

3.2. Robustness checks

We examine the robustness of the estimate to the monotonicity assumption (Angrist and Imbens, 1995). The reason for testing the robustness to this assumption is that an instrument that satisfies the relevance and validity assumptions might still yield a biased causal estimate (De Chaisemartin, 2017), due to the presence of defiers in the sample. Defiers are units that did not respond to the instrument. In this study, these are individuals that qualify for the grant, have the necessary documentation but are not receiving the grant. Or individuals that do not have the documents but are benefiting from the grant. De Chaisemartin (2017) shows that in the presence of defiers, the effect estimate may become misleading since the effect estimate under this condition is the weighted difference between the effect of the treatment between the compliers and defiers. Defiers are present in many practical application of IV (De Chaisemartin, 2017) and this study is not an exception.

For example, to mitigate the delay caused by lack of identity document, regulation 11(1) was introduced in 2008. Under this regulation, applicants who lack the prescribed documentation can use alternative documentation to apply for the CSG. These alternative documents include affidavits and a range of documentation proving the identity of the applicant (e.g., affidavit from respected community members and school report cards). Therefore, it is possible that some of the non-ID holders report benefiting from the grant. In the presence of defiers (i.e., under the violation of the monotonicity assumption), the LATE can be identified under the following conditions: (1) there exists a subpopulation of compliers of equal size to the population of defiers and (2) the defiers and the subpopulation of compliers have the same average treatment effect (De Chaisemartin, 2017, Olivo-Villabrille, 2021). If these conditions are satisfied, then the IV estimate can be interpreted as the effect for the rest of the population of compliers. The latter is referred to as surviving-compliers by De Chaisemartin (2017) as they are compliers who "out-survive" defiers or "comvivors".[7] De Chaisemartin (2017) illustrates how to estimate the worst-case bounds for the treatment effect of comvivors (see the appendix for details). If the estimated effect lies within this bound, then assumption (1) and (2) are valid and the effect estimate can be interpreted as the effect of treatment on comvivors.

The results of this analysis are presented in Table 3. Table 3 shows that the estimate is robust to the presence of defiers.

The approach of Nevo and Rosen (2012) is used to examine the robustness of the estimate to possible violation of the validity assumption. The authors show that one can replace the zero-covariance assumption required for validity of the instrument ($\rho_{instrument,\varepsilon} = 0$) with an assumption regarding the sign of the covariance between the instrument and the stochastic error and estimate bounds for the IV estimate. To operationalize their approach Nevo and Rosen (2012) make

[7] See appendix A.2 of Olivo-Villabrille (2021) for technical summary of the main ideas in De Chaisemartin (2017).

Table 3
Test of the comvivor's LATE identification assumptions.

	Stunting
p_1	0.171
p_0	0.702
$\mathbb{E}[Y\|D=1,Z=1,U_{11}\leq p_1]$	0.00
$\mathbb{E}[Y\|D=0,Z=0,U_{00}\geq 1-p_0]$	0.403
$\mathbb{E}[Y\|D=1,Z=1,U_{11}\geq 1-p_1]$	1.000
$\mathbb{E}[Y\|D=0,Z=0,U_{00}\leq p_0]$	0.000
$\underline{L}$	−0.403
$\overline{L}$	1.000
Estimate	−0.31

the following assumptions

$$\rho_{instrument,\varepsilon}\rho_{CSG,\varepsilon}\geq 0$$

$$|\rho_{CSG,\varepsilon}|\geq|\rho_{instrument,\varepsilon}|$$

These are referred to as assumptions 3 and 4 in Nevo and Rosen (2012). As noted earlier, if caregiver motivation is the omitted variable captured by the stochastic error ε then both assumptions are reasonable in our application. Further, since we have $|\rho_{CSG,instrument}|>0$, only a one sided bound can be constructed (Clarke and Matta, 2018). The procedure also produces confidence interval for the estimated bounds (Clarke and Matta, 2018). We estimate the bounds and confidence limit for the effect estimate, with and without assumption 4. The upper bounds and limits are (−0.313; −0.031) and (−0.13; −0.034) with and without assumption 4 respectively. Since the estimate of the upper bounds and the confidence limits are negative and bounded away from zero with or without assumption 4, this suggests that our substantive interpretation to the IV result is robust to violation of the validity assumption made about possession of an ID.

Lastly, we re-estimate the effect under the CIA assumption, the result is presented in column 2 of Table 4. For this analysis we use the entropy balancing method (Hainmueller, 2012). This approach produces observation weights that balances the distribution of covariates across treatment arms. We use similar covariates to the one used for the IV analysis. In addition, based on the approach adopted in extant literature, we estimate caregiver motivation (Oyenubi, 2021). The result of the entropy weighted analysis is substantively consistent with the IV results. Stunting is 14 % lower in the treated sample. We note that our IV result may suggest that relying on the CIA leads to an underestimation of the effect estimate. However, we note that the treatment effect estimated under the two methods (IV and propensity score weighting) are different. The IV approach estimates the Local Average Treatment Effect (LATE) while the entropy balancing approach estimates the Average Treatment Effect on the Treated (ATT). Therefore, these estimates are not comparable.

We use the Oster (2019) approach to investigate the magnitude of the potential bias in the entropy weighted regression. The approach is based on two regression equations: a controlled regression i.e. a regression that include the independent variable of interest (CSG receipt) and all other controls; and an uncontrolled regression, which is a regression of the outcome on the CSG receipt dummy alone. Inference is based on the parameter δ which is the coefficient of proportionality between observed and unobserved selection. If observed selection is more important than unobserved selection, then $\delta>1$ and one could conclude that the result is robust to unobserved selection. This inference is based on the proportional selection assumption, under this assumption $\delta=1$ (i.e. observables and the unobservables are equally important in determining the value of β[8]). Therefore, $\delta\geq 1$ implies that the degree of selection on unobservables will have to be larger than degree of selection on observables to nullify the results. However, to calculate δ the parameter R_{max} needs to be specified. R_{max} is the theoretical maximum R-squared from the full model where all observed and unobserved variables are included. Extant literature assumes $R_{max}=1.3\widetilde{R}$ and then use

Table 4
OLS results.

		Entropy balance
Grant recipient		−0.14**
		(0.06)
Primary caregiver characteristics	Married	−0.14***
		(0.05)
	Education: Degree	−0.24**
		(0.1)
	Employed	0.18***
		(0.05)
	Age	0.01***
		(0)
	Primary Caregiver is child's Mother or Father	0.05
		(0.05)
Child characteristics	Male gender	0.07*
		(0.04)
	Underweight	0.14*
		(0.07)
	Black	−0.17**
		(0.07)
	Child has had a Serious Illness/ Disability	0.25**
		(0.07)
	Child has been ill for at least 3 days in the last month	−0.09*
		(0.11)
	Age in years	−0.02
		(0.02)
Household Characteristics	Flush toilet	−0.04
		(0.04)
	Rural residence	−0.04
		(0.05)
	Electricity	−0.1
		(0.09)
	Male household head	0.02
		(0.04)
	Dwelling type: apartment	−0.18**
		(0.08)
	Dwelling quality: dilapidated	0.08
		(0.06)
	Dwelling type: informal dwelling	−0.17***
		(0.05)
	Household per capita expenditure	−0.00***
		(0)
Wave 4		0.06
		(0.04)
Motivation		0.05
		(0.03)
Constant		0.34**
		(0.16)
Observations		5,587
R-squared		0.23

Robust standard errors in parentheses.
Estimation is clustered at household level.
*** p < 0.01, ** p < 0.05, * p < 0.1.

[8] the assumption that $\delta=1$ is based on the fact that observed covariates are the most important in explaining the outcome since they are selected based on theory and empirical evidence (Bryan et al., 2022; Oster, 2019).

these estimates to to bound β or calculate δ (see Bryan et al, (2022) for example), in our application we consider the extreme case of the $R_{max} = 1$. Specifically, we conclude that the value of β is unlikely to be nullified by unobserved factors if $R_{max} = 1$ and $\delta \geq 1$.

For the weighted regression $\delta = 772$, which means unobserved selection will need to be 722 times stronger than observed selection for the estimated effect to be null. We conclude that the result under CIA is unlikely to be nullified by unobserved selection.

4. Discussion

In this paper, we evaluate the impact of the CSG on the stunting of South African children aged five years and younger. Unlike existing literature on this topic, we use more recent data and a method that is robust to unobserved factors. Further, we check the robustness of the estimated effect to various assumptions about the estimator. We find causal evidence that the roll-out of the CSG has had a statistically significant impact on the nutrition or stunting of children in this age group. The effect is large, as we find that stunting among benefiting children 31 % lower compared to the population of qualified but non-benefiting children. This result show that similar substantive result in the extant literature is robust to unobserved factors and that the result is valid in the more recent data. We also show that the substantive result is robust to the validity and monotonicity assumptions required for identification under the IV framework. Given the size and number of beneficiaries of the South African social assistance programmes, this finding is crucial in contributing to the literature regarding the role that the CSG plays in improving the welfare of children.

The South African grant system has received renewed attention with the onset of COVID-19 pandemic, which has threatened the livelihoods and food access of South Africans. In response, the South African government increased the Child Support Grant and rolled out a new Social Distress Relief Grant (Köhler and Bhorat, 2020). This has been met by calls from civil society for an establishment of a Basic Income Grant (Institute for Economic Justice, 2021, The Black Sash, 2021). This shift has increased the importance of assessing the effectiveness and the causal impact of the South African social assistance programmes.

One of the barriers to effective evaluation of government policies like the CSG is the non-randomised roll-out of these programmes. The lack of randomization means that we are unable to attribute improvements in stunting to the roll-out of the CSG since other unobserved or unmeasurable factors coulr bias the results. While other authors have typically dealt with this issue by relying on the Conditional Independence Assumption, we use the instrumental variable approach relying on government issued document as an instrument to evaluate the impact of the grant on stunting. This approach deals with the main limitation of the Conditional Independence Assumption, which requires that all relevant factors that affect treatment status and the outcome are controlled for in the study. Using the instrumental variable approach, we are able to provide unbiased and causal evidence of the impact of the CSG on stunting.

The CSG presents a unique opportunity for crucial early investment in childhood development. Provision of social assistance in the first two years of life result in a significant reduction of stunting. Intervening during the first two years of life is crucial given the difficulty in recovering from stunting. A study by Casale (Casale, 2020) found that even though some recovery from stunting or catch-up growth after two years of age is possible, these children still attain fewer years of schooling due to higher failure rates.

5. Conclusion

Given the relatively high rates of stunting among children in South Africa, this study highlights the importance of continued support to households living in poverty and a need to have policy action that enhance complementary factors. The economic consequences of the COVID-19 pandemic are likely to heavily affect poverty and child nutrition of South African households, which may be partially mitigated by the South African social assistance programmes.

Ethics approval and consent to participate: Ethics approval for the NIDS-CRAM Survey was granted by the Commerce Faculty Ethics Committee of the University of Cape Town and the Research Ethics Committee: Social, Behavioral and Education Research, of the University of Stellenbosch.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data availability statement included

Appendix

De Chaisemartin (2017) show that if the stated assumptions are satisfied, then it is possible to estimate worst-case bounds for the treatment effect of comvivors. To do this the author first note that wald estimator can be written as

$$W = \frac{\Pr(C)\mathbb{E}[Y_1 - Y_0|C] - \Pr(F)\mathbb{E}[Y_1 - Y_0|F]}{\Pr(C) - \Pr(F)}$$

where Y_d is the outcome under treatment $d \in \{0, 1\}$, C represents the compliers and F represents defiers. In addition, let Z be the binary instrument, then the treatment effect for the comvivors has the bounds

$$\underline{L} \leq W \leq \overline{L}$$

where

$$\underline{L} = \mathbb{E}[Y|D = 1, Z = 1, U_{11} \leq p_1] - \mathbb{E}[Y|D = 0, Z = 0, U_{00} \geq 1 - p_0]$$

$$\overline{L} = \mathbb{E}[Y|D = 1, Z = 1, U_{11} \geq 1 - p_1] - \mathbb{E}[Y|D = 0, Z = 0, U_{00} \leq p_0]$$

and $p_d = \frac{FS}{\Pr(D=d|Z=z)}$, U_{dz} is the rank of an observation in the distribution of $Y|D = d, Z = z$). $FS = \Pr(C_V)$ where C_V is the population of comvivors (De Chaisemartin, 2017; Olivo-Villabrille, 2021).

The validity of the stated assumptions then relies on the treatment effect lying between $\underline{L}$ and $\overline{L}$ (De Chaisemartin, 2017; Olivo-Villabrille, 2021).

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