Essays on Social Protection and Human Welfare in Southern Africa

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The candidate confirms that the work submitted is his own and that appropriate credit has been given where reference has been made to the work of others.

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Abstract

The potential of social protection to ensure well-being and food security in Southern Africa is gaining renewed interest in the presence of unprecedented shocks such as the COVID-19 pandemic and the incessant climate-change induced disasters. This study investigates the impact of social protection on welfare in Southern Africa and is comprised of three papers. In the first paper, I analyzed whether the Foster Care Grant in South Africa has an impact on child health. Based on five waves of the National Income Dynamics Study, the findings indicate that the grant improves height-for-age z-score by 0.23 standard deviations for children who received the grant compared to their counterpart and by 0.14 standard deviations for children who received the grant twice compared to those that received it only once. However, there is no further marginal impact for girls who receive the grant twice when compared to those that receive it only once. In the second paper, I assessed the impact of social capital on food security in Zimbabwe based on Zimbabwe Vulnerability Assessment Committee data, finding that households with social capital are more food secure and are more likely to receive agricultural extension services. In the third paper, I assessed the impact of social protection and the Special COVID-19 Social Relief of Distress Grant on hunger in South Africa. Based on two waves of the National Income Dynamics Study - Coronavirus Rapid Mobile Survey, the findings indicate that receiving a government grant reduces the likelihood of going hungry and running out of money to buy food by 6 and 12 percentage points respectively, and receiving the special COVID-19 Social Relief of Distress Grant lowers chances of child hunger. Further, the findings indicate no heterogeneity on hunger between those that were screened or tested for COVID-19 and those who were not.

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List of Abbreviations

ATT	Average Treatment Effect on the Treated
CRE	Correlated Random Effects
FCG	Foster Care Grant
FNC	Food and Nutrition Council
IPTW	Inverse Probability of Treatment Weights
NIDS	National Income Dynamics Study
NIDS-CRAMS	National Income Dynamics Study-Coronavirus Rapid Mobile Survey
NGOs	Non Governmental Organisations
PSM	Propensity Score Matching
ZIMVAC	Zimbabwe Vulnerability Assessment Committee

CHAPTER 1

INTRODUCTION

1.1 Background and Motivation

The potential of social protection to provide care, fight poverty and contribute toward inclusive growth in Southern Africa is gaining renewed recognition, particularly in the presence of unprecedented shocks such as the COVID-19 pandemic and the incessant climate change-induced disasters that leave communities extremely vulnerable. These shocks are associated with deterioration of welfare with households being thrown into sustained periods of food insecurity, children not receiving adequate care and the general erosion of social fabric. In desperate situations such as these, poor households, individuals and communities may only have formal or informal social protection as their last resort.

Social protection comprises actions adopted as a result of vulnerability, risks, and deprivation (see e.g. Niño-Zarazúa et al., 2012) or a combination of formal or informal tools which empower households to fight and reduce vulnerability, risk and cope with economic shocks. Social protection in Southern Africa is diverse with complex and interesting dynamics. In Zimbabwe, for example, because of weak formal systems, vulnerable members of society draw upon informal initiatives that rely on traditional social networks such as family, neighbours, membership in a social group and community solidarity, self-organization and reciprocity. On the other hand, South Africa is characterized by formal social protection systems that are guided by statutes and laws, institutionalized in policy and legislation as well as funded by government with delivery centered on national priorities and eligibility criteria. Both formal and informal mechanisms of social protection in Southern Africa aim to address deep-seated vulnerabilities through either cash transfers or social capital (see e.g. Barrientos et al., 2013; Devereux, 2013; Hajdu et al., 2020; Mupedziswa and Ntseane, 2013; Mendola, 2017; Toska et al., 2016).

This study empirically assesses the impact of social protection on welfare in Southern Africa, with emphasis on South Africa and Zimbabwe. South Africa was chosen mainly because it is the only country in Southern Africa with a comprehensive formal social protection system reaching to millions of beneficiaries and cutting across almost all layers of vulnerable members of society. It is a possible model for other relatively wealthier Southern African countries such as Botswana and Namibia (see e.g. Devereux, 2013) and its influence has been fundamental in the diffusion of social protection systems to neighbouring countries such as Lesotho and Eswatini (see e.g. Niño-Zarazúa et al., 2012). On the other hand, Zimbabwe was chosen because of the relative uniqueness of its circumstances characterized by weak formal systems, a majority of people living outside the formal sector with irregular, unpredictable incomes and little to no chance of making any contributions towards social security as well as the prevalence of informal social protection organized according to behavioural principles of reciprocity, affective relationships, and community bonding.

One group of vulnerable members of society in South Africa is children, 50 percent of whom live below the poverty line. These children normally suffer from chronic malnutrition (see e.g. Modjadj and Madiba, 2019; Nyati et al., 2019) which is the underlying cause for half of South Africa's childhood deaths. In general, malnutrition is typically caused by a combination of inadequate food intake and associated infections that may result in low food conversion efficiency (Hough and Sosa, 2015; Jensen et al., 2017). This includes challenges such as stunting, wasting, and inadequacies of essential vitamins and minerals as well as obesity (Ayllon and Ferreira, 2015). For example, 1.5 million children in South Africa are stunted and 75,000 are obese.

Other relevant characteristics such as appropriate care, parental education, access to quality health care, as well as living environment and household food security are important in the health production function of a child. To that effect, however, height-for-age is generally used as a measure of children's additive development and therefore reflects a child's history and present inadequate nutrition. Early childhood development, as measured by height-for-age for example, is therefore of paramount importance. Lack of cumulative development in the early years of children's lives may lead in the long term to poor cognitive development, reduced adult size, and undermined labour outcomes in adulthood (Deaton, 2008). This is where cash transfer programs are becoming important as vehicles of human capital development.

1.1.1 Chapter 2: The Impact of the Foster Care Grant on Child Health in South Africa

The second Chapter of this thesis assesses the impact of the Foster Care Grant on child health in South Africa. Specifically, the chapter seeks to answer the following question: Does a Foster Care Grant have an impact on child health in South Africa? The grant is an unconditional cash transfer, which provides temporary, substitute, away-from-home care to vulnerable children whose families cannot provide it within a safe and nurturing environment. The grant is an interesting case study in many respects. Compared to almost all unconditional cash transfers in Africa, the Foster Care Grant is relatively more generous. This is important because this has implications for the range and intensity of impacts on food security and nutrition outcomes.

The Foster Care Grant is unique in that it caters for children up to the age of 17 and in some cases even up to the age of 22 under special circumstances. This brings in another dimension of catch-up that is often ignored in the literature (see Hirvonen, 2014; Leroy et al., 2009; Lundeen et al., 2014; Porter and Goyal, 2016; Prentice et al., 2013; Schott et al., 2013). Surprisingly, this grant has not been subjected to rigorous evaluations and has not received much attention. Although there has been an interest in assessing the impact of unconditional cash transfers on food security, nutrition and health in Africa, this study presents an interesting opportunity to better understand the long-term impact of unconditional cash transfers on health since the Foster Care Grant has been around for over 20 years compared to many unconditional cash transfers in Africa. For example, Miller et al. (2011) evaluation in Malawi was short-term, conducted over the course of one year.

Based on five waves of the nationally representative National Income Dynamics Study (NIDS) and Correlated Random Effects, Hybrid Model and Propensity Score Matching estimations, the study provides the following findings. First, there is a positive and significant program and program intensity impact of the Foster Care

Grant on height-for-age for children in South Africa. The grant improves height-for-age z-score by 0.23 standard deviations for children who received the grant compared to their counterparty and by 0.14 standard deviations for children who received the grant twice compared to those that received it only once. However, when disaggregated by gender, there is no further marginal impact for girls who receive the grant twice when compared to those that receive it only once. This is an important result with serious policy implications. Boys experience both significant program and program intensity impacts. Since there is a provision for extension of the Foster Care Grant benefit after the initial two years, accessing the grant more than once can therefore be encouraged for boys, where circumstances allow, since it leads to program intensity impacts. Furthermore, the findings indicate no program intensity and program impact of the Foster Care Grant on weight-for-age, implying that the program appeals to the long-term human capital development through height-for-age as opposed to short-term changes in nutritional status.

1.1.2 Chapter 3: Coping Strategies, Agricultural Extension Services and the Impact of Social Capital on Food Security in Zimbabwe

When vulnerability is mentioned in Southern Africa, food insecurity, a perennial challenge for many households in Zimbabwe, always comes up. This results from a number of factors ranging from droughts, climate change (see e.g. Govere et al., 2020; Nyagumbo et al., 2019) to land tenure. Some parts of Zimbabwe have become synonymous with drought (Belle, 2017; Mavhura, 2017) and flood-related disasters (Gwimbi, 2007) which destroy crops, livestock and hopes, resulting in food insecurity. Coupled with lack of appropriate agricultural technologies and little research and development as well as heterogeneity in productivity created by land reform and its migration from large scale commercial farms to small and medium land holding, many households are left at the mercy of food insecurity.

Unlike South Africa, with its comprehensive formal social protection systems, Zimbabwean households fall back on their social networks and other coping strategies to ensure survival. In light of this, this study empirically assesses the impact of social capital on food security in Zimbabwe by addressing whether households with members belonging to a social group are more likely to be food-secure and less likely to go hungry; less likely to adopt behavioral hunger-coping strategies; more likely to receive and seek agricultural extension services; and more likely to treat harvests against post-harvest losses, than those without. Although there is work on social capital, much of the work on social capital and coping strategies in Southern Africa tend to focus on climate change (see e.g. Mbiba et al., 2019; Nagoli et al., 2017). This research is distinct in that it adds to the extant literature by assessing the impact of social capital on food security in Zimbabwe based on a quasi-experimental approach.

Drawing on 2015 nationally representative data collected by the Zimbabwe Vulnerability Assessment Committee (ZIMVAC) and employing Propensity Score Matching, the findings show that households with social capital are more food secure. More specifically, households with members belonging to a social group such as community associations, informal savings and loans associations, agricultural extension groups, credit unions for inputs and burial societies are less likely to engage in demanding, psychologically stressful behavioural hunger-coping strategies such as skipping meals, limiting portion size of meals and reducing number of meals eaten. Households with members belonging to a social group have a 7 percentage point lower chance of experiencing a day with no food to eat, a 4 percentage point lower chance of going to sleep at night hungry, a 5 percentage point lower chance of limiting portion size of meals and a 5 percentage point lower chance of reducing number of meals eaten; compared with households without members belonging to a social group. Furthermore, households with members belonging to a social group are more likely to seek and to receive agricultural extension services than those without these social networks.

The results also show that households with social capital are more likely to preserve their harvest against post-harvest losses. For example, social capital increases the chances of receiving agricultural training, seeking crop advice, and treating harvests against post-harvest losses by 23, 17, and 14 percentage points, respectively. This ensures food security. These results have important policy implications. For a country with weak formal social protection systems as well as recurrently experiencing persistent climatic shocks ranging from droughts to devastating tropical cyclones, self-organization, reciprocity and informal, traditional social protection systems in the form of social capital ensure food security. This may also mean that other food security interventions may ride on existing informal social structures since intended beneficiaries value the collective functioning of the society.

1.1.3 Chapter 4: The Impact of Social Protection and the Special COVID-19 Social Relief of Distress Grant on Hunger in South Africa

An understanding of vulnerability and food security also needs to be gained in relation to the COVID-19 pandemic. In Southern Africa, in general, the pandemic coincided with other existing shocks such as adverse climatic effects in Zimbabwe (Ejeromedoghene et al., 2020) and thus it amplified the threats to food security. However, food insecurity coping strategies usually common in countries like Zimbabwe such as social networks for support in the form of sharing meals with neighbours and family are difficult due to lockdowns and social distancing restrictions. This increases the importance of a robust safety net led by the state. To that effect and considering the potential policy implications for the whole region, the study empirically assesses the impact of social protection and the Special COVID-19 Social Relief of Distress Grant on Hunger in South Africa.

Based on Correlated Random Effects estimations employed on two waves of the National Income Dynamics Study – Coronavirus Rapid Mobile Survey (NIDS-CRAM), which is the first nationally representative panel data survey investigating the socioeconomic impacts of the national lockdown in South Africa, the findings show that receiving a government grant reduces the likelihood of going hungry and running out of money to buy food by 6 and 12 percentage points, respectively. This is an important finding. This means that countries with a strong safety net system are likely to be better prepared to contain COVID-19-induced food insecurity. COVID-19 pandemic is associated with prolonged periods of restrictive measures, severe income shocks, and disruption of traditional coping strategies. For many vulnerable members of society, government grants may be the only coping strategy available.

The results also indicate that receiving the Special COVID-19 Social Relief of Distress Grant lowers chances of child hunger. This is an important finding too. The fact that there is no impact of the Special COVID-19 Social Relief of Distress Grant on overall household hunger but an impact on child hunger may reflect altruism on the part of adults. Adults may skip meals in order to make sure children get enough to eat. However, the results indicate that the Special Unemployment Insurance Fund benefit does not have an impact on hunger and does not cushion individuals and households from running out of money to buy food; possibly pointing to the need to pay special attention to each type of social protection and its accessibility to ensure its effect is maximized.

1.2 Structure of the Thesis

The rest of the thesis is organized as follows. Chapter 2 investigates the impact of the Foster Care Grant on child health in South Africa. Chapter 3 assesses the impact of social capital on food security in Zimbabwe while Chapter 4 investigates the impact of social protection and the Special COVID-19 Social Relief of Distress Grant on hunger in South Africa. Finally, Chapter 5 concludes the thesis, provides some policy implications and identifies potential areas for further research.

CHAPTER 2

THE IMPACT OF THE FOSTER CARE GRANT ON CHILD HEALTH IN SOUTH AFRICA

2.1 Introduction

Cash transfers have become a respected development tool with potential to fight intergenerational poverty through investments in human capital development (Rawlings and Rubio, 2005). They are targeted interventions providing cash to selected beneficiaries (Manley et al., 2013); particularly disadvantaged and vulnerable members of society. Child nutritional investments can have a significant impact on human capital attainments (Potter and Goyal, 2016) and there is a sustained interest to find out the extent to which social protection impacts child health and nutritional outcomes.

Vulnerable children normally suffer from malnutrition which is typically caused by a combination of inadequate food intake and associated infections that may result in low food conversion efficiency (Hough and Sosa, 2015; Jensen et al., 2017). This includes challenges such as stunting, wasting, and inadequacies of essential vitamins and minerals as well as obesity (Ayllon and Ferreira, 2015). Other relevant characteristics such as appropriate care, parental education, access to quality health care, as well as living environment and household food security are important in the health production function of a child. Early childhood development is of paramount importance and lack of cumulative development in the first years of children's lives is caused by inadequate diet and incessant infections, which in the long term may lead to poor cognitive development, reduced adult size, and undermined labour outcomes in adulthood (Deaton, 2008). This is where cash transfer programs are becoming important as vehicles of human capital development.

Most of what is known about the impact of cash transfers on food security, nutrition and health comes from well-documented experiences of mostly Latin American countries (e.g.Attanasio and Mesnard, 2005; Galaso, 2011; Hidrobo et al., 2018; Hidrobo et al., 2015; Fiszbein et al., 2014; Gertler et al., 2012; Manley et al., 2013;

Morris et al., 2004). Cash transfer programs in Africa are relatively new development phenomena with most programs in their pilot stages and covering a few thousand beneficiaries. Most of these programs are unconditional as opposed to the experiences drawn from Latin American countries. Results from the relatively few unconditional cash transfer programs are mixed and in some cases disappointing (Himaz, 2008; Potter and Goyal, 2016; Ruel et al., 2013). For example, Kirk et al. (2018) used rural samples of three waves of the Uganda National Panel Survey and estimated panel regressions of child height-for-age z-scores controlling for time-invariant child-level heterogeneity and found no impact of short-term changes in total gross income on height-for-age z-scores.

On the other hand, Fisher et al. (2017) examine whether and how cash transfers go beyond welfare objectives to promote livelihoods using evidence from six Sub-Saharan African countries concluding that a small but predictable flow of cash improves strategic livelihood choices and stimulates productive investments. Similarly, Tiwari et al. (2016), working on evidence from four Sub-Saharan African countries also found that a relatively generous, regular and predictable transfer increases the quantity and quality of food and reduces the prevalence of food insecurity.

This study contributes to the growing and interesting literature on cash transfers in general and on the impact of unconditional cash transfers from Africa in particular. Although Fisher et al. (2017) looked at a cross-country analysis of the impact of cash transfers on livelihoods in Sub-Saharan Africa, their focus was on Kenya, Ethiopia, Malawi, Lesotho, Zimbabwe and Ghana. Related, a cross-country analysis of the impact of unconditional cash transfers in Sub-Saharan Africa by Tiwari et al. (2016) focused on Ghana, Kenya, Lesotho and Zambia. Yet, South Africa is a very interesting case study as far as social protection programs are concerned. It has a comprehensive social protection system for all vulnerable members of the society (children, the elderly, disabled, and war veterans) with beneficiaries running into several thousands and in some cases into millions.

The Foster Care Grant in South Africa is an unconditional cash transfer, which provides temporary, substitute, away-from-home care to vulnerable children whose families cannot provide them with a safe and nurturing environment. The obligations of the foster parent are to ensure that the child's welfare is adequately taken care by making sure that the child is fed, clothed, healthy, and attending school. Remarkably, notwithstanding its monetary generosity, the grant has not been subjected to rigorous evaluations nor received much attention. On the other hand, most of the health and nutrition grants target children up to 3 years old and in some cases up to the time they enrol in primary school. The Foster Care Grant is unique in that it caters for children up to the age of 17 and in some cases even up to 22 under special circumstances. This brings in another dimension of catch-up that is often ignored in the literature (see Hirvonen, 2014; Leroy et al., 2009; Lundeen et al., 2014; Porter and Goyal, 2016; Prentice et al., 2013; Schott et al., 2013). For example, Rieger and Wagner (2015) found that children can partially catch-up from malnutrition spells; suggesting that sustainable nutrition interventions have to be long term.

Improvements in living conditions brought about by adoption may trigger catch-up growth among vulnerable children. Therefore, the Foster Care Grant may lead to improvement in nutritional status for foster children and ultimately may lead to improved health outcomes. A natural question is: Does a monthly transfer of cash in the form of a Foster Care Grant have a positive impact on child health? I hypothesized that the Foster Care Grant has an impact on height-for-age, weight-for-age, and body mass index for vulnerable children in South Africa that have been placed in foster care.

The arrangement of the rest of this Chapter is as follows. The next section details the background to the Foster Care Grant. Section 2.3 presents a review of relevant strands of the literature and clarifies the hypotheses to be tested whilst section 2.4 provides the data and descriptive analysis. Section 2.5 specifies the methodology. Section 2.6 and 2.7 specifies balancing and estimation results, respectively. Finally, section 2.8 concludes.

2.2 Background of the Foster Care Grant

The Foster Care Grant is a social protection program in South Africa intended to provide for the basic needs of children who have been placed in the care of foster parents by a Children's Court. The grant is paid to the foster parent for children aged between 0 and 18 years with a possibility of an extension to until the age of 21 years if the child is still in secondary school. It provides temporary, substitute, away-from-home care to vulnerable children whose families cannot provide them with a safe and nurturing environment. The obligations of the foster parent are to ensure that the child's welfare is adequately taken care by making sure that the child is fed, clothed, healthy, and attending school. This means that the foster parent must be a sustainable family or individual willing to act as foster parents to the child and must have capacity to provide an environment that is conducive to the child's growth and development.

The grant is usually for two years with a provision for extension for a further two years subject to assessment by a social worker given compelling circumstances. Eligibility criteria for Foster Care Grant require that the foster parent and the foster child must be resident in South Africa at the time of making an application but not necessarily citizens. This means that a child from any country that is in South Africa and in need of care and protection can be fostered; including undocumented and refugee children. Importantly, the would-be foster parent must be in possession of a court order that makes the foster care status legal. This means that the child must have been placed in foster care by order of the court before the Foster Care Grant can be sought.

Circumstances are dynamic and as a result a social worker regularly reviews the situation of a child who is placed in foster care to determine whether the foster child remains in the care of the parents; is fed, clothed, and receives necessary medical attention; and goes to school regularly. The Foster Care Grant can be terminated if the foster child or both foster parents pass away; the child is no longer in the custody of the foster parent; and when the court order expires as well as when the child turns 18 and when the child leaves school at school leaving age.

The value of the Foster Care Grant is R 1,050 (USD 70) per eligible child per month. This is an important figure considering that monthly food poverty line in South Africa is at R 561 (USD 37) per person per month. The poverty line refers to the amount of money that a person requires to get the minimum required daily energy intake. The grant amount is greater than the lower-bound poverty line which is currently at R 810 per month per person and not so far off from the upper-bound poverty line at R 1,227 per person per month. The lower-bound poverty line refers to the food poverty line plus the average amount derived from non-food items of households whose total expenditure is equal to the food poverty line. On the other hand, the upper-bound poverty line refers to the food poverty line plus the average amount derived from non-food items of households whose food expenditure is equal to the food poverty line. The grant is a third of the median wage in South Africa which is put at R 3,300, a figure that is reported to support 3.5 people. This goes to show how important the Foster Care Grant is in fighting poverty.

The Foster Care Grant is very generous when compared to other child grants in South Africa. For example, it is almost 2.4 times greater than the Child Support Grant which is a means-test social protection program given to a primary caregiver for children under the age of 18 who do not receive any other social assistance from the government and who do not receive any care from a state institution. Elsewhere in Southern Africa, Zambia's Child Grant gives a child 70 Kwacha (ZMW) which is equivalent to USD11 per month. The Lesotho Grant Program pays varying amounts depending on the number of children and it pays per quarter as opposed to monthly. It pays M360 for a household with 1 to 2 children, M600 for 3 to 4 children, and M750 for 5 or more children. The Lesotho Lot (M) is pegged at 1:1 with the South African Rand (R). Therefore the Foster Care Grant is very generous when compared to many child grants in Southern Africa.

The Foster Care Grant, in South Africa, is not a new phenomenon having been in existence since the early 1960s. However, the number of beneficiaries never rose above 40,000. Only after South Africa gained independence in 1994 did the Foster Care Grant experienced relative phenomenal growth. By the year 2000, a total of almost 50,000 beneficiaries received court-ordered foster care; 120,000 by the year 2004; and the figure skyrocketed to slightly above 450,000 by 2008. In February 2017, the number of beneficiaries reached 478,158 (South African Human Rights Commission/UNICEF,2011; Factsheet, 2017). The Foster Care Grant has become an important case both in terms of coverage and importance that warrants interrogation to assess the impact of a social protection program that has been in the backwaters of rigorous evaluation.

2.3 Literature review and hypotheses

Cash transfer programs have proved to be an important development tool for poverty alleviation in developing countries (Bazzi et al., 2015; Davis et al., 2016; Hanlon et al., 2010; Jensen et al., 2017). They are a form of a social protection mechanism with long-term potential for breaking intergenerational poverty through promoting human capital development (Barrientos, 2012; Fisher et al., 2017; Robertson et al., 2013); through investments in vulnerable children's health and education. Cash transfers have also proved to be life-sustaining for vulnerable social groups and households in the face of shocks (Hur et al., 2010) by improving availability, access and utilization of food during crisis (Handa et al., 2014; Maluccio, 2005; Miller et al., 2011; Tiwari et al., 2016).

Most of what is known about the impact of cash transfers on food security, nutrition and health comes from well-documented experiences of mostly Latin American countries (e.g.Attanasio and Mesnard, 2005; Galaso, 2011; Hidrobo et al., 2018; Hidrobo et al., 2015; Fiszbein et al., 2014; Gertler et al., 2012; Manley et al., 2013; Morris et al., 2004). In particular, Hidrobo et al. (2018) reviewed 66 studies on food security and concluded that social protection programs improve both the quantity and quality of food consumed by beneficiaries. Most of the experiences from Latin America comprise conditional cash transfer programs; and have registered success in improving nutritional status. For example, Oportunidades in Mexico improved child growth (see Fernald et al., 2009; Manley et al, 2013; Gertler, 2004; Gertler, 2000; Rawlings and Rubio, 2005; Rivera et al., 2004); *Bono de Desarrollo Humano* in Ecuador (Paxson and Schady, 2010) and *Familias en Accion* in Colombia (Attanasio et al., 2005) improved height of preschool children. Leroy et al., (2009) assessed evidence on the impact of Conditional Cash Transfers on child nutrition and discovered significant improvements in child anthropometrics. Lopez-Arana et al., (2016) evaluated the effect of *Familias en Acciion* (FA) on children's stunting, body mass index, thinness, overweight and obesity and discovered reduced odds of thinness; with prevalence of stunting, overweight and obesity decreasing over time. However, no impact on height-for-age was observed.

In a comprehensive study, Manley et al. (2013) analysed evidence on the relationship between cash transfer programs and nutritional status of children in recipient households and found that the programs' average impact on height-for-age is positive; albeit small and not statistically significant. Besides, they discovered that girls tend to benefit more than boys. The issue of gender heterogeneity in the impact of cash transfers on health outcomes is widely noted. For example, girls may see larger benefits than boys from cash transfers (Duflo, 2003). Related, the issue of kinship and caregiver characteristics has also been under scrutiny. For example, Ayllon and Ferreira-Batista (2015) studied the relationship between single motherhood and children's height-for-age z-score in Brazil. They paid attention to the role of the gender of the first-born and a low sex ratio to marital status and found out that single mothers that have been affected by giving birth to first-born girl child with a low sex ratio have a height-for-age z-score that is lower than that of children of similar characteristics that cohabit with both progenitors.

Elsewhere, Himaz (2008) found that the largest social assistance program in Sri Lanka, which is aimed at integrating youth, women, and disadvantaged groups into economic and social development, as well as promoting social stability and alleviating poverty, improves height-for-age z-score of a child from a grant-receiving family by roughly 0.40 standard deviations with the impact led by children between six, and 36 months of age, in comparison to those that did not receive the grant. In the case of weight-for-height, the results show an improvement of 0.45 standard deviations for children aged 36 – 60 months.

Cash transfer programs in Africa are relatively new development phenomena with most programs in their pilot stages and covering a few thousand beneficiaries. Most of these programs are unconditional as opposed to those from Latin American countries. Although conditional cash transfers are popular, questions have been raised on the importance of conditionalities (Barrientos, et al., 2010); with arguments centred on the supply-side constraints emanating from lack of sufficient health infrastructure for example. This means that conditional cash transfers may not be the best option in circumstances where access to health facilities is poor, which is true in most African countries. In such situations, unconditional programs are more likely to deliver improved welfare.

Porter and Goyal (2016) investigated the impact of the Productive Safety Net Program, a large-scale social protection scheme in Ethiopia, on child nutritional outcomes. The Productive Safety Net Program is a safety net introduced in 2005 which is designed to provide predictable support to selected food insecure households over several years. In their analysis, they focused on the effect of the program on individual child nutritional status as measured by height-for-age. Their results show an important positive medium-term nutritional impact of the program for children aged 5-15 years that is comparable in size to Conditional Cash Transfer program impacts for much younger children. They went on to show expressive evidence that the program impact on improved nutrition is identified with improved food security and reduced child working hours.

In rural Malawi, Miller et al. (2011) found sizeable program impact of the Malawi Social Transfer Cash Transfer Scheme on food security and food diversity. On the other hand, the Zambia Child Grant and the Zambia Multiple Category Cash Transfer Program (both unconditional) were found not to reduce perceived stress but improve economic security as measured by per capita consumption expenditure, food insecurity, and asset ownership (Hjelm et al., 2017). In general, some of the unconditional cash transfers and pilot programs in Africa have exhibited positive impacts on food expenditure and consumption (Gillian et al., 2013; Haushofer and Shapiro, 2014; Merttens et al., 2013). An unconditional cash transfer for orphans and vulnerable children in Kenya was found to reduce the likelihood of early pregnancy of adolescent girls (Handa et al., 2015); as well as contributing to higher household economic security and overall wellbeing (Handa et al., 2014). It was also found to reduce depressive symptoms (Kilburn et al., 2015).

This study contributes to the growing and interesting literature on cash transfers in general and on the impact of unconditional cash transfers from Africa in particular. Although Fisher et al. (2017) looked at a cross-country analysis of the impact of cash transfers on livelihoods in Sub-Saharan Africa, their focus was on Kenya, Ethiopia, Malawi, Lesotho, Zimbabwe and Ghana. Relatedly, a cross-country analysis of the impact of unconditional cash transfers in Sub-Saharan Africa by Tiwari et al. (2016) focused on Ghana, Kenya, Lesotho and Zambia. Yet, South Africa is a very interesting case study as far as social protection programs are concerned.

South Africa, as mentioned above, has a comprehensive social protection system for all vulnerable members of society (children, the elderly, disabled, and war veterans) with beneficiaries running into several thousands and in some cases into millions. The Foster Care Grant, in particular, is an interesting case study in many respects. It gives a foster child R 1,050 (USD 70 equivalent) per month per foster child. Surprisingly, the Foster Care Grant has not been subjected to rigorous evaluations and has not received much attention. South Africa in general, and the Foster Care Grant in particular is an interesting case study in terms of coverage and grant amount. Compared to almost all unconditional cash transfers in Africa, the Foster Care Grant is relatively more generous. This is important because this has implications for the range and intensity of impacts on food security and nutrition outcomes. Although there has been an interest on assessing the impact of unconditional cash transfers on food security, nutrition and health in Africa, this study presents an interesting opportunity to better understand the long-term impact of unconditional cash transfers on child health since the Foster Care Grant has been around for over 20 years compared to many unconditional cash transfers in Africa. For example, Miller et al. (2011) evaluation in Malawi was short-term, conducted over the course of one year.

There is little that has been written on unconditional cash transfers in South Africa in general and the Foster Care Grant in particular. Previous studies of cash transfer programs' impact on child nutritional status in South Africa are limited despite comprehensive social protection programs for children. Notable, however, is Duflo (2003) who assessed the impact of the Old-Age Pensions on children's nutritional status. Booysen and Van Der Berg (2005) did not give insights into how food expenditures change as households become income-grant recipients when they examined income sources and food expenditures among a population of HIV affected households and non-affected controls. This research is distinct and aims to add value to the body of knowledge by bridging the gap on the Foster Care Grant. The question that arises is whether the Foster Care Grant leads to consumption gains that are reflected by improved health outcomes for foster children.

Testable Hypotheses

Cash transfer programs are important for human capital development. In some cases, they are the only source of income and provide food security for poor households and vulnerable children. There is a powerful connection between early childhood nutrition and health status and subsequent economic success (Hoddinott et al., 2008). A strong correlation between ill-health, malnutrition, under-nutrition, and poverty and chronic poverty (Krishna, 2007; Lentz and Barrett, 2013) exists. Vulnerable children such as orphaned and neglected children are more likely to suffer from ill-health, mal- and under-nutrition, which is associated with reduced human capital accumulation, including below average adult stature, poor cognitive capacity, and reduced economic productivity and lower adult earnings, among others. This implies that low and poor investment in human capital accumulation leads to inter-generational transmission of poverty. For example, mothers who were themselves undernourished as children are more likely to give birth to low weight children (see Behrman et al., 2009; Victoria et al., 2008).

Although other factors such as household preferences and intra-household dynamics are important for a guarantee in children nutritional improvements, the importance of a regular cash transfer cannot be underestimated. Cash transfer programs, in some cases, have been found to have a positive effect on child height (see Labrecque et al., 2018; Rivera et al., 2004). In the case of the Foster Care Grant in South Africa, the obligations of the foster parent are to ensure that the child's welfare is adequately looked after by making sure that the child is fed, clothed, healthy, and attending school. The Foster Care Grant, therefore, may lead to improvement in nutritional status for foster children and ultimately may lead to improved health outcomes. I therefore propose the following hypotheses linking the impact of the Foster Care Grant to child health outcomes:

Hypothesis 2.1:

The Foster Care Grant has an impact on child health for foster children in South Africa.

2.4 Data

This study draws on the National Income Dynamics Study (NIDS), which is South Africa's first nationally representative panel data. It is a comprehensive longitudinal study, which investigates livelihood dynamics, coping strategies and well-being of households and individuals over time by examining changes in household composition and structure, poverty and demographics. It also follows and details economic activity and labour market issues, human capital development on health and education as well as changes in social capital and social protection programs. The NIDS is a rich dataset with detailed child, adult and household level panel information.

The data has five waves, as detailed in Table 2.1 below. The data has four anthropometric variables namely: height-for-age; weight-for-age; weight-for-height; and body mass index z-scores. Each child was measured on these variables three times in order to minimize or eliminate the chances of errors and as such the variables are relatively highly reliable.

Table 2.1: National Income Dynamics Study (NIDS) – Number of Observations

	Households	Adults	Children	Total Observations
Wave 1 (2008)	7,296	16,871	9,606	31,144
Wave 2 (2010)	9,127	21,880	11,081	36,156
Wave 3 (2012)	10,219	22,466	12,216	42,150
Wave 4 (2015)	11,889	26,804	13,971	49,532
Wave 5 (2017)	13,719	30,110	14,993	52,361

Table 2.2 presents descriptive statistics for the entire dataset as well as for 2008, 2010, 2012, and 2015 datasets. The average age for a child is 7 and about 50 percent of the children are girls; while 89 percent are black. Thirty-eight percent of the children live in urban areas. A cross-wave average of 3.7 percent of the children is

receiving the Foster Care Grant. The average age of the household head is 50 with an average of 6 years of education. On average, the household size in the dataset is 7 and 69 percent of households are female-headed.

On the other hand, Table 2.3 below presents descriptive statistics for the outcome variables. The average height-for-age z-score is -1.17, -0.76, and -0.83 for children aged 1-4, 5-9, and 10-14 years respectively. The summary statistics for weight-for-age and body mass index z-scores are detailed in the same Table.

Table 2.2: Descriptive Statistics for Covariates

VARIABLES	Full Sample Mean (sd)	2008 Mean (sd)	2010 Mean (sd)	2012 Mean (sd)	2015 Mean (sd)
Child's Age	7.09	6.83	7.18	7.23	7.04
	(4.09)	(3.95)	(4.11)	(4.10)	(4.13)
Girl	0.50	0.50	0.50	0.51	0.51
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Head's Education	5.98	5.06	5.50	6.42	6.43
	(4.49)	(4.41)	(4.59)	(4.60)	(4.25)
Head's Age	50.31	52.50	51.14	48.22	50.32
	(15.61)	(15.01)	(15.45)	(15.89)	(15.60)
Head is Female	0.69	0.58	0.68	0.753	0.69
	(0.46)	(0.49)	(0.46)	(0.43)	(0.46)
Household Size	7.0	6.75	7.27	7.06	6.87
	(3.63)	(3.25)	(3.95)	(3.78)	(3.45)
Foster Care Grant	0.04	0.03	0.03	0.03	0.04
	(0.19)	(0.18)	(0.18)	(0.18)	(0.20)
Child is black	0.89	0.89	0.90	0.89	0.89
	(0.31)	(0.31)	(0.30)	(0.32)	(0.32)
Geo Area: Urban	0.38	0.35	0.36	0.38	0.40
	(0.49)	(0.48)	(0.48)	(0.49)	(0.49)
Observations	31,023	5,377	6,991	8,470	10,185

Notes: SD = Standard errors; are in parenthesis.

Table 2.3: Descriptive Statistics for Outcome Variables

Panel A:

VARIABLES	Full Sample Mean (sd)	2008 Mean (sd)	2010 Mean (sd)	2012 Mean (sd)	2015 Mean (sd)
Height-for-age	-0.897	-0.873	-0.973	-0.919	-0.858
	(1.426)	(1.453)	(1.493)	(1.557)	(1.267)
Weight-for-age	-0.284	-0.367	-0.264	-0.231	-0.294
	(1.248)	(1.292)	(1.308)	(1.292)	(1.159)
Body Mass Index	0.379	0.244	0.473	0.473	0.331
	(1.429)	(1.442)	(1.532)	(1.531)	(1.279)
Observations	22,427	4,069	3,594	6,447	8,317

Panel B:

VARIABLES	Full Sample Mean (sd)	1 – 4 years Mean (sd)	5 – 9 years Mean (sd)	10 – 14 years Mean (sd)
Height-for-age	-0.897	-1.173	-0.755	-0.829
	(1.426)	(1.532)	(1.235)	(1.219)
Weight-for-age	-0.284	-0.237	-0.345	-0.438
	(1.248)	(1.232)	(1.236)	(1.209)
Body Mass Index	0.379	0.733	0.141	-0.0344
	(1.429)	(1.453)	(1.312)	(1.313)
Observations	22,427	8,704	12,415	436

Notes: SD = Standard errors; are in parenthesis.

2.5 Methodology

Impact evaluations are carried out to determine the difference between an outcome with intervention and the outcome without the intervention. However, a major challenge mostly encountered in impact evaluations is that one cannot observe a counterfactual for participants had they not participated. Comparing outcomes of participants to those of people who did not participate in the intervention results in biased estimates due to potential selection bias arising from unobserved characteristics correlated with the outcome. For example, children whose parents or caregivers with higher intellectual capacity are more likely to receive the Foster Care Grant than those whose caregivers are less intelligent. Accessing the Foster Care Grant involves a court order and foster parents with a strong legal understanding are more likely to access the grant than those without.

In other cases, the bias may not arise due to individuals self-selecting into treatment, but from being selected for treatment on the basis of an interview or evaluation of their willingness to cooperate with the program giving rise to administrative selection bias or program placement bias. The issue of selection bias is not a challenge where participants are selected randomly; but full randomised selection is not always available. Access to the Foster Care Grant is not based on randomisation but rather on eligibility and in the National Income Dynamics Study (NIDS), baseline data for the Foster Care Grant is not available for intervention evaluation. The standard Difference-in-Differences method cannot be applied, and Instrumental Variables approach are likewise unavailable for want of plausible instruments. For the purpose of this study, and given that the NIDS is a panel data with 5 waves, three identification strategies namely Correlated Random Effects; Hybrid; and Propensity Score Matching models are adopted.

2.5.1 Correlated Random Effects

The Correlated Random Effects (CRE) model is selected for its several benefits. First, it circumvents the disadvantages of Fixed-Effects models by estimating within effects in Random-Effects models (Allison, 2009; Schunck, 2013). It can lead to the use of time-invariant fixed effects in a linear model, and simple robust tests of correlation between heterogeneity and explanatory variables. It introduces extra parameter heterogeneity and provides two over-identifying restrictions that can be tested in the data (Wooldridge, 2019). In our case, it allows for heterogeneity in the returns to receiving the Foster Care Grant and decomposes the cross-sectional bias for each child separately. For each child, the CRE gives a parameter that shows the partial correlation between background characteristic effect and receiving the Foster Care Grant. The model is applied here to a relationship in which specific unobserved background and household characteristics such as a taste for healthy children and child high food conversion efficiency are of particular concern.

Second, CRE models can also allow the estimation or identification of average partial effects as opposed to just parameters. They do not suffer from over-parameterization problems (Suryadipta, 2017; Woodridge, 2010; 2011; 2018). The general model specification adopted is as follows:

$$h_{it} = g_t\theta + z_i\delta + F_{it}\varphi + w_{it}\vartheta + \alpha_i + \mu_{it} \qquad (1)$$

where:

h_{it} is health outcome for child *i* at time *t* denoting height-for-age, weight-for-age and body mass index z-scores. Height-for-age was chosen because it is widely regarded as the main indicator of nutritional status (see Manley et al., 2013; WHO, 1986, 1995, 2006), which reflects long term human capital development. It is of particular interest because it is a good proxy for cumulative nutritional status (Himaz, 2008; Labrecque et al., 2018; Rieger and Wagner, 2015). It is documented in the literature that improvements in height-for-age z-scores may be due to an improvement in past nutritional status and may improve health and cognitive outcomes later in life. On the other hand, weight-for-age indicates shorter-term changes in nutritional status.

g_t captures a vector of aggregate time effects corresponding to the wave year; z_i is a set of time-invariant observed covariates such as gender, race, geographical area, and child health status; F_{it} captures the Foster Care Grant status for child *i* at time *t*; w_{it} is a vector of time-varying covariates; α_i captures child fixed effects and μ_{it} is an idiosyncratic error. Equation 1 above is then transformed to become a Correlated Random Effects (CRE) model by allowing time-constant variables as follows:

$$h_{it} = g_t\theta + z_i\delta + F_{it}\varphi + w_{it}\vartheta + \omega + \overline{w_i}\gamma + \alpha_i + \mu_{it} \qquad (2)$$

In other words, the CRE equation (2) supplements the Fixed Effects equation (1) by estimating a linear projection of the unobserved heterogeneity onto covariates. In particular, interest is on estimators of φ that allow for correlation between α_i and the history of covariates, $\{w_{it} : t = 1, \dots\dots\dots, T\}$. The CRE approach enables the unification of fixed and random effects estimation approaches. This specification follows proposal by Mundlak (1978) who projected the unobserved heterogeneity onto the mean of the explanatory variables; and which was later relaxed by Chamberlain (1980, 1982). The main assumption here is that:

$$\in [\alpha_i \backslash w_{i1}, \dots \dots \dots, w_{iT}] = \in [(\alpha_i \backslash \bar{w}_i) = \omega + \bar{w}_i \gamma] \qquad (3)$$

By assumption, Equation (3) is expected to be linear and a sufficient condition. It is important to note that $\bar{w}_i = T^{-1} \sum_{t=1}^{T} w_{it}$ is a vector of time averages. From Equation (3), γ estimates the between-group effect. Note that at times a group mean may be included to obtain the within effect of ϑ in order to ensure that effect estimates of level 2 variables are corrected for between-group differences in w_{it} (see Schunck, 2013). As highlighted above, there are quite a number of advantages for taking this approach, which include an opportunity to test for equivalence of within-group and between-group estimates; can be used with generalized equations enabling specification of less restrictive within-group structures; and can be extended to allow for effects of level 1 variables to vary between clusters by including random slopes.

2.5.2 Hybrid Model

The hybrid model extends the Correlated Random-Effects model by including random slopes thereby allowing effects of level 1 variables to vary between groups. The Correlated Random-Effects model uses the undemeaned level-one variables captured by w_{it} . Although it is possible to include random slopes with a purely Correlated Random-Effects model, it is not equivalent to the corresponding Hybrid model with random slopes; in which case it is highly recommended to use the Hybrid model (see Schunck, 2013). The Hybrid model also allows for the inclusion of level 2 variables as well as capable of being used with generalized estimating equations.

The Hybrid model used in this study is specified as follows:

$$h_{it} = \beta_0 + (\beta_1 + \mu_{2i})(w_{it} - \bar{w}_i) + \beta_2 \alpha_i + \beta_3 \bar{w}_i + \mu_{1i} + \varepsilon_{it} \qquad (4)$$

The Hybrid model works by splitting within- and between-group effects for level-one covariates by including both the deviation from the cluster-specific mean of the time-varying covariates and the cluster-specific mean $\bar{w}_i$ From Equation 4, β_1 yields the within-group effect, and β_3 captures the between-group effect.

The Hybrid and Correlated Random-Effects models are preferred here over the Fixed-Effects and Random Effects models because they are flexible and separate within- and between- group effects. They permit consistent estimation of level-one effects and the inclusion of level-two variables (see Schunck and Perales, 2017). They combine the strengths of Random- and Fixed-Effects models by yielding level-one estimates that are unbiased by cluster-level unobserved heterogeneity and at the same time permitting level-two cluster-invariant explanatory variables.

2.5.3 Propensity Score Matching

As in many real-world applications, where it is not feasible to assign participants to treatment alternatives, observational studies are the only viable options (Rosenbaum, 2002, 2010; Lechner, 2000; Lee, 2017). In that case therefore other methods which deal with selection on unobservables have to be adopted. This study also uses Propensity Score Matching (PSM) to estimate causal treatment effects. PSM is used here to build a statistical counterfactual group that is based on a model of the probability of participating in the Foster Care Grant using observed characteristics.

The specification is as follows. Defining the number of times a child received Foster Care Grant as ϑ (treatment) when compared with φ (control) number of times the child received the Foster Care Grant (where $\vartheta > \varphi$ and can take the value of 0 but not necessarily means zero), the average impact of the Foster Care Grant will be given by:

$$ATT^{\vartheta,\varphi} = E\left[Y^{\vartheta} - Y^{\varphi}\middle|D = \vartheta\right] = E\left[Y^{\vartheta}\middle|D = \vartheta\right] - E[Y^{\varphi}|D = \vartheta] \qquad (5)$$

As Moreno-Serra (2005) argued, a specification of this nature leads to an Average Treatment Effect on the Treated (ATT) equivalent to the marginal gain in terms of an outcome. In the context of this study, it is a marginal gain in terms of height-for-age, weight-for-age, and body mass index accruing to a randomly selected child who received the Foster Care Grant ϑ times relative to what would have been the outcome if the child had received the Foster Care Grant φ times in the four time periods.

The major assumptions in a specification of this nature are weak unconfoundedness and overlap. This captures the assumption of ignorability (Rosenbaum and Rubin, 1983). The first assumes that covariates that affect receiving the Foster Care Grant have been measured in the study. On the other hand, the second is based on an assumption that every child has a probability greater than zero of receiving Treatment or Control. The probability of assignment is bounded away from zero and one as follows:

$$0 < \Pr(D = 1 | X, \vartheta, \varphi) < 1 \qquad (6)$$

where D = 1 is receiving the Foster Care Grant a specified number of times in the four time periods. This is the assumption of common support, which ensures that there is ample overlap in the characteristics of the treatment and the control for adequate matches. This means that for each value of X, there is a positive probability of being both treated and untreated. This way, therefore, would allow for a balanced distribution in measured important baseline covariates in the compared groups.

2.5.4 The experiment

In designing the experiment, the study uses two Control Groups. The first Control Group (which is conveniently called Control Group 1) is comprised of children who received the Foster Care Grant only once in the whole time period. This yielded a total of 1,567 children who received the Foster Care Grant only once in the four time periods (i.e. Control Group 1: n = 1,567). The second Control Group (Control Group 2) is comprised of children whose caregivers never received the Foster Care Grant in the four time periods and from the data, a total of 42,119 such children never received the Foster Care Grant in the four time periods (i.e. Control Group 2: n = 42,119).

The Treatment Group is comprised of children whose caregivers received the Foster Care Grant twice in the four time periods and this yielded a total of 504 children (i.e. Treatment Group: n = 504). Designing the two Control Groups against this Treatment Group also provides a platform to check robustness of the results. The choice of this treatment group is motivated by specifications in the regulation of the grant in which it is categorically stated that the grant is usually for two years with a provision for extension for a further two years subject to assessment by a social worker given compelling circumstances.

2.6 Balancing results

2.6.1 *Estimating Propensity Score*

In estimating a model of program participation, samples of children who received the grant once (T = 0) and those that received twice (T = 1); as well as those that did not receive any grant (T = 0) and those that received it twice (T = 1), were pooled to estimate participation on observed covariates that are likely to determine participation. The specification of the participation equation used is as follows:

$$FCG_i = \alpha + \tau W_i + \beta X_i + \varepsilon_i \tag{7}$$

where FCG_i stands for Foster Care Grant status and is binary reflecting $T = 1$ or $T = 0$ for a child; W_i is a vector for interaction and higher order terms and X_i is a vector of other explanatory variables. The model is estimated using probit and the predicted outcome from the participation equation is therefore the probability of participation or the propensity score. Results of this probit model are presented in Table 2.4 below. Arguably, all the variables chosen in the calculation of the propensity score are associated with both the treatment and outcomes. For example, the Child's Age is definitely associated with height-for-age (for example) and in turn associated with the Foster Care Grant. The younger the child the more likely there is a change in anthropometric outcomes, and the younger the child the more likely the family is to receive the Foster Care Grant but not necessarily in a causal way. The Household Head's Education, for example, is associated with health outcomes.

Table 2.4: Probit Results on Program Participation

	(1)	(2)
Child's Age	0.167***	-0.0269
	(0.0308)	(0.0349)
Child's Squared Age	-0.00580***	0.00837***
	(0.00178)	(0.00217)
Household Head's Age	0.00946***	0.00315
	(0.00173)	(0.00243)
Household Head is Female	0.123**	-0.179**
	(0.0506)	(0.0722)
Household Head's Education	0.0237***	0.0359***
	(0.00621)	(0.00890)
Race: Black	-0.182**	-0.0623
	(0.0709)	(0.1000)
Geo-Area: Urban	-0.0288	-0.105
	(0.0512)	(0.0704)
Household Size		-0.00159
		(0.00947)
Constant	-3.769***	-0.526**
	(0.187)	(0.246)
Observations	29,484	1,775

Standard errors in parentheses. ***Significant at 1%; **Significant at 5%; *Significant at 10%. Estimations in Column (1) are based on a sample comprising of children who never received the Foster Care Grant and those that received the grant twice; and estimations in Column (2) are comprised of children who received the grant once and those who received the grant twice.

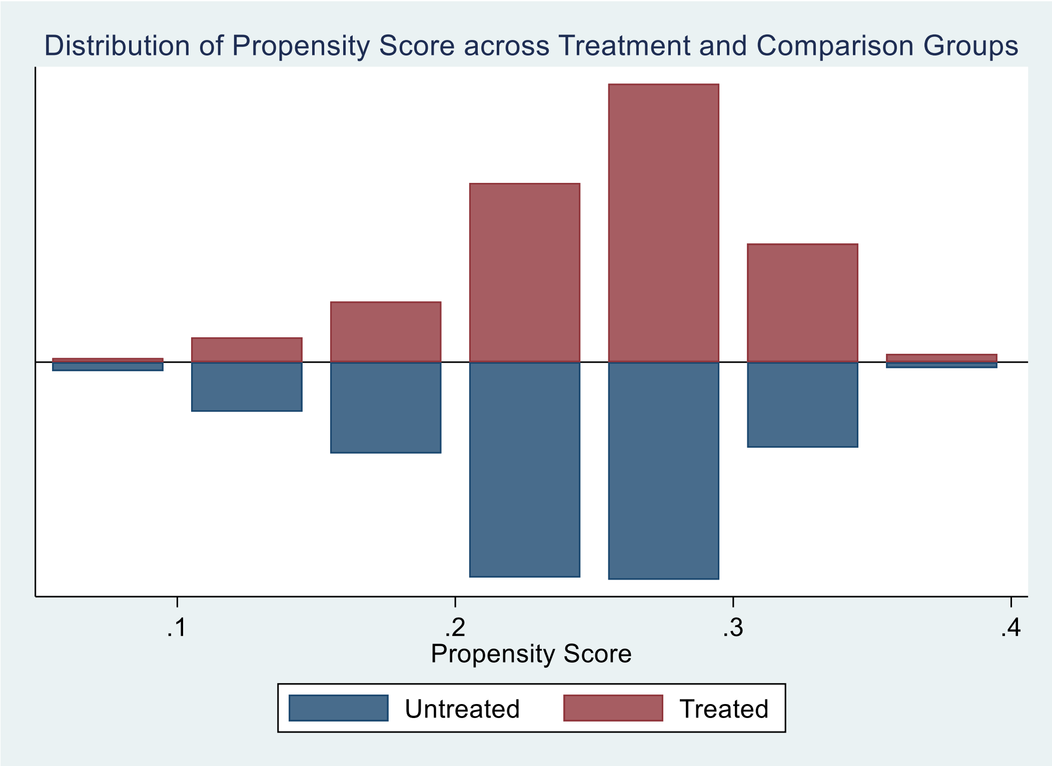
The more educated the household head is the more likely it will be for her to have a higher taste for healthier children. Likewise, the more educated the household head is, the more likely he or she will better understand the requirements for applying for the Foster Care Grant including understanding court proceedings that are used to determine eligibility. To improve the estimation and balancing, also included is the Square of the Child's Age.

In order to achieve strong ignorable treatment assignment, a rich set of covariates was used by excluding variables that are related to treatment but not the outcome and variables that may be influenced by the treatment (see, Lee and Little, 2017; Imbens, 2004) as well as those that perfectly predict treatment status. Excluding variables that perfectly predict treatment status is important because distributions of covariates need to overlap between treatment and comparison groups. On the other hand, variables affected by treatment obscures part of the treatment effect that is being estimated (see, Ho et al., 2007); and variables associated with treatment but not outcome add noise to the estimate and thereby reduce precision. Importantly too, including too many covariates was avoided since over-specification can result in higher standard errors for the estimated propensity score.

2.6.2 Balance on the propensity score

In order to generate confidence in the estimates, there is need for considerable overlap in the propensity scores between treatment and comparison groups. The idea is to make sure that no inference about treatment effects can reasonably be made for a treated child for whom there is not a comparison child with the same propensity score. This can be achieved by subjectively assessing the common support using graphs of propensity scores across treatment and control groups. Figure 2.1 below shows the distribution of propensity score across Treatment and Comparison Groups and it can be concluded that the extent of the overlap is quite satisfactory.

Figure 2.1: Distribution of Propensity Score across Treatment and Comparison Groups



Notes: Treated = Children whose caregivers received the Foster Care Grant twice in the four time periods. Comparison (Untreated) = Children whose caregivers received the Foster Care Grant only once in the four time periods.

2.6.3 Balance on the Covariates

It is also important to check for balance of individual covariates across treatment and comparison groups within blocks of the propensity score after the propensity score is balanced. Balance on covariates assures that the propensity score is correctly specified and that its distribution is not different across groups within each block. Table 2.5 shows the covariate balance across Treatment and Comparison Groups after the Inverse Probability of Treatment Weights (IPTW) on the propensity score based on Control Group 1, which is comprised of children whose caregivers received the Foster Care Grant only once.

Table 2.5: Covariate Balance across Treatment and Comparison Groups after the Inverse Probability of Treatment Weights (IPTW) Matching on the Propensity Score using Control Group 1

	…………Inverse Probability of Treatment Weights		
Variable	*Mean Treatment (n = 504)*	*Mean Comparison (n = 1567)*	*Standardized Difference (%)*
Child's Age	8.61	8.66	-0.014
Child's Age Squared	88.36	88.72	-0.006
Household Head's Age	54.14	54.07	0.004
Household Head is Female	0.72	0.73	-0.014
Household Head's Education	5.81	5.80	0.003
Race – Black	0.86	0.86	-0.008
Geo-Area : Urban	0.42	0.41	0.019

Notes: Control Group 1 is comprised of children who received the Foster Care Grant only once in the four time periods. The Treatment Group is comprised of children who received the Foster Care Grant twice in the four time periods.

In turn, covariate balance across Treatment and Comparison Groups after Inverse Probability of Treatment Weights (IPTW) Matching for Control Group 2, which is comprised of children whose caregivers never received the Foster Care Grant in the four time periods is presented in Table 2.6. It is important to note that the small differences in means after the balance are very desirable.

Table 2.6: Covariate Balance across Treatment and Comparison Groups after the Inverse Probability of Treatment Weights (IPTW) Matching on the Propensity Score using Control Group 2

	…………..Inverse Probability of Treatment Weights		
Variable	*Mean Treatment (n = 504)*	*Mean Comparison (n = 42 119)*	*Standardized Difference (%)*
Child's Age	6.97	7.35	-0.097
Child's Age Squared	67.11	70.79	-0.061
Household Head is Female	0.63	0.66	-0.055
Household Head's Education	6.60	6.61	-0.001
Geo-Area: Urban	0.44	0.41	0.050
Household Size	6.77	6.78	-0.001

Notes: Control Group 2 is comprised of children who did not receive the Foster Care Grant in any of the four time periods. The Treatment Group is comprised of children who received the Foster Care Grant twice in the four time periods.

Table 2.7 to Table 2.10 below show covariate balance between treatment and control groups using Nearest-Neighbour matching (with and without caliper) since the Inverse Probability of Treatment Weights (IPTW) matching of covariate balance across treatment and control groups does not show standardized difference between Treatment and Control Group before matching. These descriptive results show standardized differences before and after matching.

Table 2.7: Covariate Balance across Treatment and Comparison Groups before and after Matching on the Propensity Score Based on Control Group 1

Variable	*....Original Sample…………. Mean Treatment (n = 504)*	*Mean Comparison (n = 1567)*	*Standardized Difference (%)*	*……Nearest Neighbor Matched Sample….. Mean Treatment (n = 504)*	*Mean Comparison (n = 1567)*	*Standardized Difference (%)*
Child's Age	8.82	8.28	14.5	9.0	8.93	1.9
Child's Age Squared	90.03	84.29	9.5	92.63	91.37	2.1
Head's Age	54.67	53.51	7.2	54.01	55.64	-10.1
Head is Female	0.71	0.72	-2.7	0.73	0.72	2.1
Head's Education	5.91	5.69	5.2	6.01	5.46	12.5
Race – Black	0.85	0.86	-0.7	0.87	0.84	8.2
Geo-Area : Urban	0.37	0.43	-11.0	0.36	0.35	0.5

Notes: Control Group 1 is comprised of children who received the Foster Care Grant only once in the four time periods. The treatment Group is comprised of children who received the Foster Care Grant twice in the four time periods.

Table 2.8: Covariate Balance across Treatment and Comparison Groups before and after Caliper Matching on the Propensity Score Based on Control Group 1

	....Original Sample…………			*……Caliper Matched Sample…..*		
Variable	*Mean Treatment (n = 504)*	*Mean Comparison (n = 1567)*	*Standardized Difference (%)*	*Mean Treatment (n = 504)*	*Mean Comparison (n = 1567)*	*Standardized Difference (%)*
Child's Age	8.82	8.28	14.5	9.0	8.93	1.8
Child's Age Squared	90.03	84.29	9.5	92.63	91.37	1.4
Head's Age	54.67	53.51	7.2	54.01	55.64	-8.8
Head is Female	0.71	0.72	-2.7	0.73	0.70	6.4
Head's Education	5.91	5.69	5.2	6.01	5.75	6.0
Race – Black	0.85	0.86	-0.7	0.87	0.85	4.1
Geo-Area : Urban	0.37	0.43	-11.0	0.36	0.36	-1.0

Notes: Control Group 1 is comprised of children who received the Foster Care Grant only once in the four time periods. The treatment Group is comprised of children who received the Foster Care Grant twice in the four time periods. The Caliper (1: 2 with replacement) was calculated as 0.2*0.0552985.

Table 2.9: Covariate Balance across Treatment and Comparison Groups before and after Nearest Neighbour Matching on the Propensity Score Based on Control Group 2

	....Original Sample…………			*……Nearest Neighbor Matched Sample…..*		
Variable	*Mean Treatment (n = 504)*	*Mean Comparison (n =42 119)*	*Standardized Difference (%)*	*Mean Treatment (n = 504)*	*Mean Comparison (n = 42 119)*	*Standardized Difference (%)*
Child's Age	8.82	6.93	48.3	8.99	8.92	1.8
Child's Age Squared	90.03	66.41	39.2	92.46	90.68	3.0
Head is Female	0.71	0.65	13.1	0.73	0.74	-2.6
Head's Education	5.91	6.72	-17.4	5.99	6.00	-0.2
Geo-Area: Urban	0.37	0.43	-12.1	0.36	0.34	3.0
Household Size	7.48	6.73	21.7	7.51	7.32	5.2

Notes: Control Group 2 is comprised of children who did not receive the Foster Care Grant in the four time periods. The treatment Group is comprised of children who received the Foster Care Grant twice in the four time periods.

Table 2.10: Covariate Balance across Treatment and Comparison Groups before and after Caliper Matching on the Propensity Score Based on Control Group 2

	....Original Sample………..			*……Nearest Caliber Matched Sample…..*		
Variable	*Mean Treatment (n = 504)*	*Mean Comparison (n =42 119)*	*Standardized Difference (%)*	*Mean Treatment (n = 504)*	*Mean Comparison (n = 42 119)*	*Standardized Difference (%)*
Child's Age	8.82	6.93	48.3	8.99	8.98	0.1
Child's Age Squared	90.03	66.41	39.2	92.46	92.0	0.8
Head is Female	0.71	0.65	13.1	0.73	0.76	-5.4
Head's Education	5.91	6.72	-17.4	5.99	6.05	-1.1
Geo-Area: Urban	0.38	0.43	-12.1	0.36	0.34	2.7
Household Size	7.48	6.73	21.7	7.51	7.25	7.5

Notes: Control Group is comprised of children who never received the Foster Care Grant in the four time periods. The Treatment Group is comprised of children who received the Foster Care Grant twice in the four time periods. The Caliper(1: 2 with replacement) was calculated as 0.2*0.0068011. SD = 0.0068011.

It is very important to check whether the treatment and comparison groups are well balanced in the matched and weighted samples. This can be achieved by subjectively assessing density functions of continuous covariates in treated and control groups plotted. Figure 2.2 to 2.4 show Density Plots after Kernel Matching based on Control Group 1. Density plots based on Control Group 2 (comprised of children whose caregivers did not receive the Foster Care Grant in any of the four time periods) are presented in Figure 2.6 to 2.8 below. The treatment and comparison are well balanced.

Figure 2.2: Density Plot of Mean Age after Kernel Matching based on Control Group 1

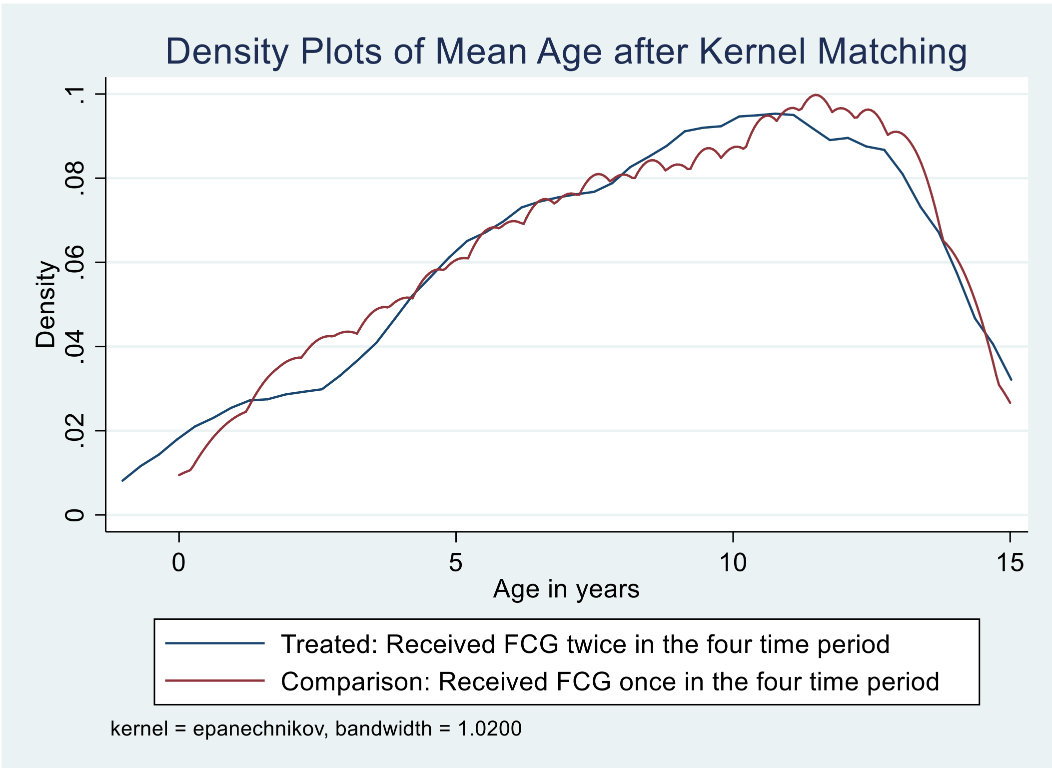


Figure 2.3: Density Plot of Mean Household Head's Age after Kernel Matching based on Control Group 1

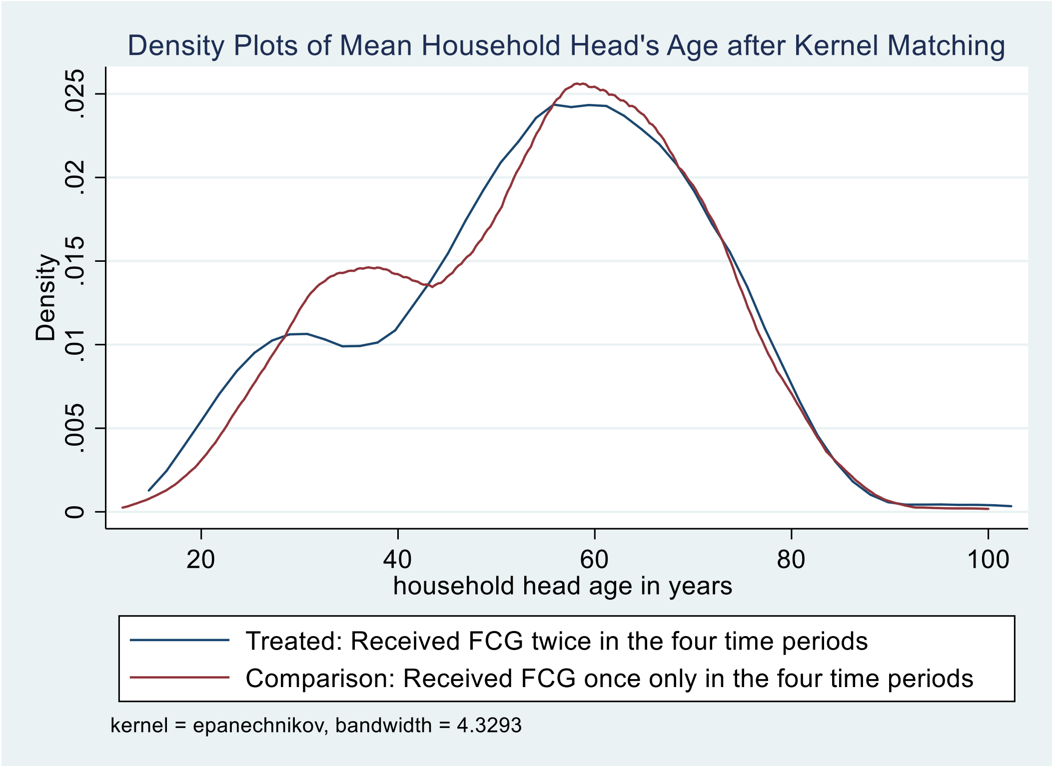


Figure 2.4: Density Plot of Mean Household Head's Education after Kernel Matching based on Control Group 1

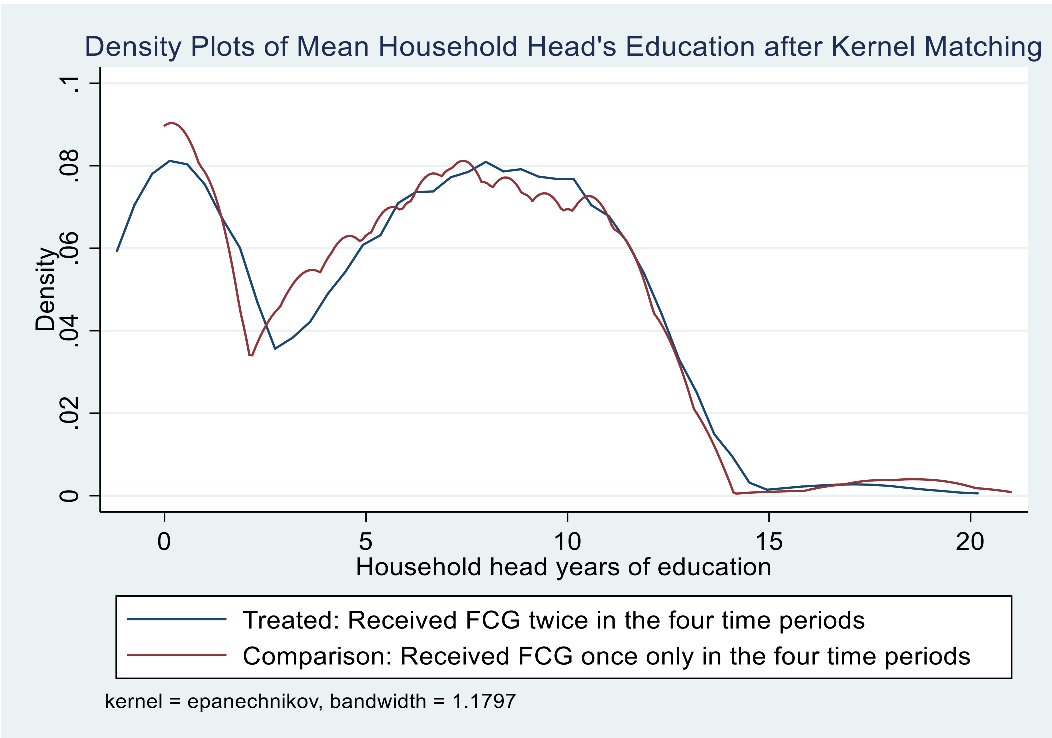
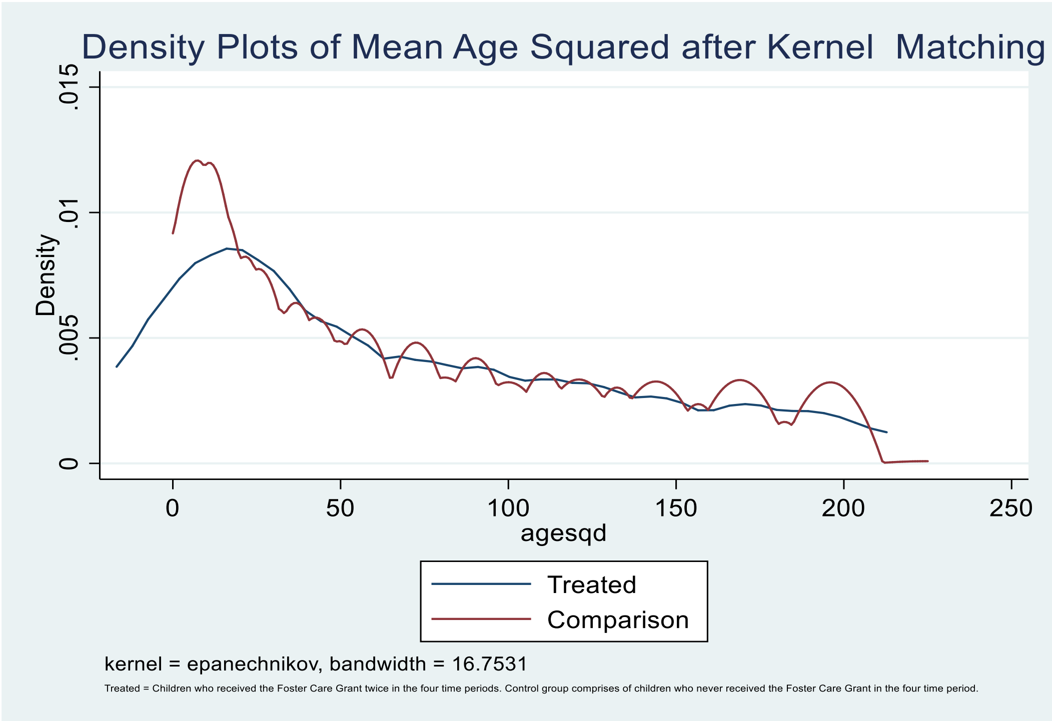


Figure 2.5: Density Plot of Mean Age Squared after Kernel Matching based on Control Group 2



Notes: Treated = children who received the Foster Care Grant twice in the four time period. Control = children who never received the Foster Care Grant in the four time period.

Figure 2.6: Density Plot of Mean Household Head's Education after Kernel Matching based on Control Group 2

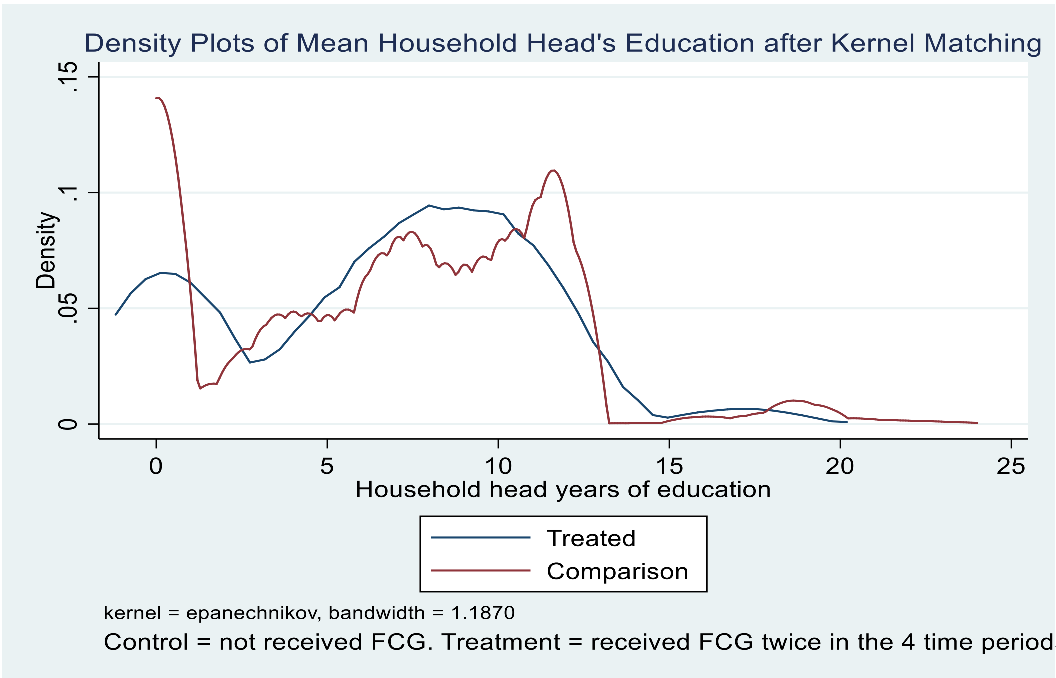
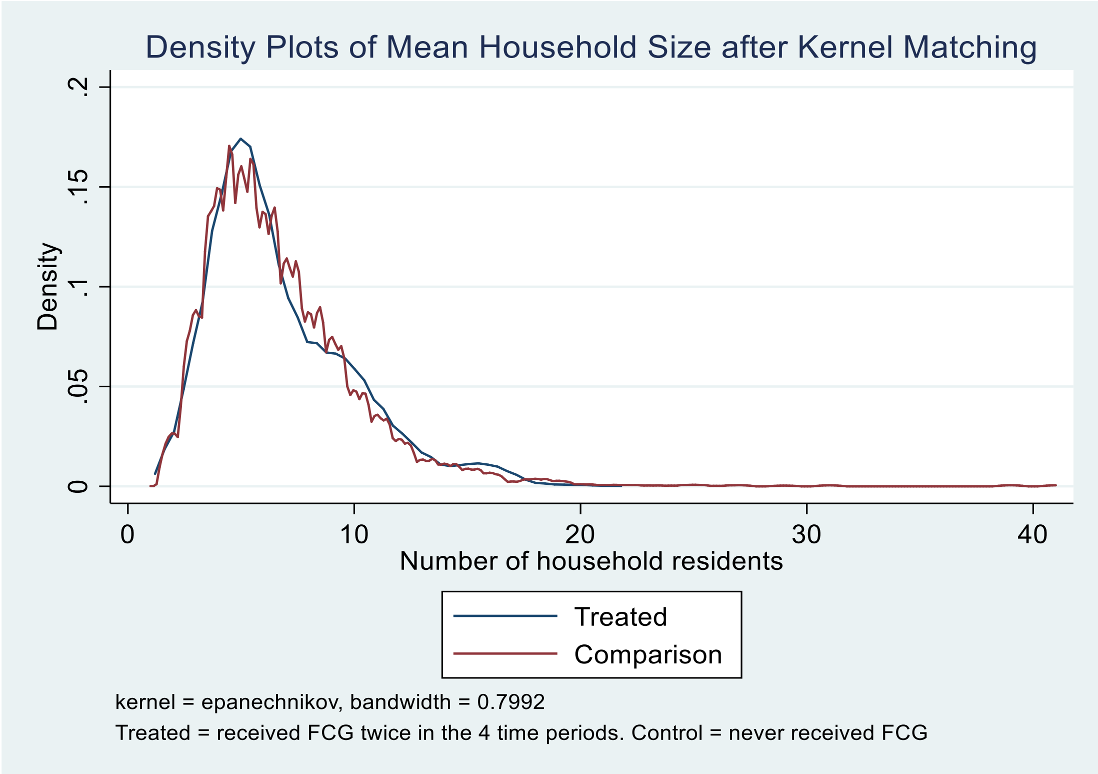


Figure 2.7: Density Plot of Mean Household Size after Kernel Matching based on Control Group 2



Notes: Treated = children who received the Foster Care Grant twice in the four time period. Control = children who never received the Foster Care Grant in the four time period.

2.7 Estimation Results

2.7.1 Propensity Score Matching Estimation Results

Estimation results are based on one treatment group and two control groups. The treatment group, as highlighted earlier, is comprised of children who received the Foster Care Grant twice in the four time period. Control Group 1 is comprised of children who received the Foster Care Grant only once in the four time period. It can be emphasized that estimations using Control Group 1 therefore tests program intensity. Control Group 2 is comprised of children who never received the Foster Care Grant in the four time period.

2.7.1.1 Program intensity

Table 2.11 below shows the Average Treatment effect on the Treated (ATT) of the Foster Care Grant on height-for-age, weight-for-age, and body mass index using propensity score matching based on the Inverse Probability of Treatment Weights (IPTW) and the Nearest Neighbour matching algorithms. Interpretation and analysis of the results is based on IPTW; and Nearest Neighbour results are presented here for robustness check only. The Foster Care Grant has a positive and significant impact on height-for-age for children aged 0-14 years. For this age group, it improves height-for-age z-score by 0.137 standard deviations for children who received the grant twice compared to those that received it only once. This confirms hypothesis 2.1 above. Disaggregating the sample by age, the results show a positive and significant impact for both children aged 1-4 years and for children aged 5-9 years. This is an important result because it shows that the Foster Care Grant has a positive and significant impact on accumulated investments in child health as measured by height-for-age. It also suggests that receiving the grant more than once has a positive impact on child health.

The results, however, do not show any significant impact on height-for-age for children aged 10-14 years. This result does not support the argument of catching-up but rather is in line with emphasis in the literature that interventions on health outcomes tend to be more effective in the early stages of a child. On the other hand, receiving the Foster Care Grant twice as compared to receiving it once does not lead to significant improvements in weight-for-age z-scores for foster children in South Africa. The results also show no significant intensity improvement on body mass index for all the age groups.

Understanding gender heterogeneity in the impact of cash transfer programs on health outcomes gives another important dimension in better interrogating who benefits and who does not and can inform on policy formulation in developing countries. Table 2.12 shows estimation results of the Average Treatment effect on the Treated (ATT) of the Foster Care Grant on girls' health using propensity score matching based on Control Group 1. Just like in Table 2.11, Control Group 1 is comprised of children who received the Foster Care Grant only once in the four time period and the Treatment Group is comprised of children who received the grant

Table 2.11: Average Treatment Effect on the Treated (ATT) of the Foster Care Grant on Child Health Using Propensity Score Matching Based on Control Group 1

	Full Sample (Children aged 0-14 years)	*Sample of Children aged 1-4 years*	*Sample of Children aged 5-9 years*	*Sample of Children aged 10-14 years*
Height-for-age				
IPTW Matching	-0.137*	-0.548*	-0.246**	-0.039
Nearest Neighbour	-0.160	-0.922***	-0.243	-0.010
Weight-for-age				
IPTW matching	0.031	-0.311	0.051	
Nearest Neighbour	-0.019	-0.071	-0.101	
Body Mass Index				
IPTW matching	-0.002	-0.216	0.072	-0.010
Nearest Neighbour	0.055	-0.133	0.250*	-0.107
Balancing property satisfied	Yes	Yes	Yes	Yes
Common support imposed	Yes	Yes	Yes	Yes
Observations				
Treated	504	57	201	241
Comparison	1567	291	561	683

Notes: Control Group 1 is comprised of children who received the Foster Care Grant only once in the four time periods. The treatment Group is comprised of children who received the Foster Care Grant twice in the four time periods.

twice in the same period. The results show that there are no program intensity impacts for girls who received the grant twice as compared to those that only received it once on height-for-age, weight-for-age, and body mass index for all the age groups.

Table 2.12: Average Treatment Effect on the Treated (ATT) of the Foster Care Grant on Girls' Health Using Propensity Score Matching based on Control Group 1

	Full Sample (Children aged 0-14 years)	*Sample of Children aged 1-4 years*	*Sample of Children aged 5- 9 years*	*Sample of Children aged 10-14 years*
Height-for-age				
IPTW Matching	-0.083	-0.524	-0.294*	0.105
Nearest Neighbour	-0.045	-0.938	-0.182	0.143
Weight-for-age				
IPTW Matching	0.018	-0.043	-0.021	
Nearest Neighbour	0.165	0.181	0.032	
Body Mass Index				
IPTW Matching	-0.104	-0.423	-0.092	-0.072
Nearest Neighbour	-0.128	-0.059	-0.140	-0.055
Balancing property satisfied	Yes	Yes	Yes	Yes
Common support imposed	Yes	Yes	Yes	Yes
Observations				
Treated	293	36	113	141
Comparison	773	147	271	337

Notes: Control Group 1 is comprised of children who received the Foster Care Grant only once in the four time periods. The treatment Group is comprised of children who received the Foster Care Grant twice in the four time periods.

On the other hand, the results in Table 2.13 on the Average Treatment effect on the Treated (ATT) of the Foster Care Grant on boys' health, show that there is a positive and significant program intensity impact on height-for-age for children aged 0-14

Table 2.13: Average Treatment Effect on the Treated (ATT) of the Foster Care Grant on Boys' Health Using Propensity Score Matching based on Control Group 1

	Full Sample (Children aged 0-14 years)	*Sample of Children aged 1-4 years*	*Sample of Children aged 5-9 years*	*Sample of Children aged 10-14 years*
Height-for-age				
IPTW Matching	-0.261**	-0.699*	-0.168	-0.340**
Nearest Neighbour	-0.157	-1.209***	-0.415**	0.023
Weight-for-age				
IPTW Matching	0.032	-0.886**	0.134	
Nearest Neighbour	-0.032	-0.435	-0.086	
Body Mass Index				
IPTW Matching	0.092	-0.034	0.273	-0.072
Nearest Neighbour	0.014*	0.294	0.261	0.127
Balancing property satisfied	Yes	Yes	Yes	Yes
Common support imposed	Yes	Yes	Yes	Yes
Observations				
Treated	211	21	88	100
Comparison	795	145	290	346

Notes: Control Group 1 is comprised of children who received the Foster Care Grant only once in the four time periods. The treatment Group is comprised of children who received the Foster Care Grant twice in the four time periods.

years; 1-4 years; and 10-14 years who received the grant twice compared to those that received it only once; by 0.26, 0.7, and 0.34 standard deviations respectively.

The significant program intensity impact for boys aged 10-14 years is evidence of catching up in long term investments in health for boys compared to girls. However, there is no impact on weight-for-age for boys for the full sample. A positive and significant program intensity impact on weight-for-age is registered for boys aged 1-4 years; with boys who received the Foster Care Grant twice witnessing an improvement in weight-for-age z-scores by 0.886 standard deviations compared to those that received the grant only once. No impact on body mass index is registered for boys of all age groups.

The results on program intensity of the Foster Care Grant on height-for-age, weight-for-age, and body mass index therefore show that there is a positive and significant impact of the grant on height-for-age for the full sample (children aged 0-14 years), for children aged 1-4 years, and for children aged 5-9 years. However, there is no impact on height-for-age for children aged 10-14 years and neither is there a significant program intensity impact on weight-for-age and body mass index for all age categories. By paying particular attention to gender heterogeneity, results show that there is a positive and significant program intensity impact for boys in all age categories including even children aged 10-14 years; and a positive and significant program intensity impact on weight-for-age for boys aged 1-4 years. However, there is no program intensity impact on height-for-age, weight-for-age, and body mass index for girls.

2.7.1.2 Program Impact

Estimations to assess the impact of the Foster Care Grant on height-for-age, weight-for-age, and body mass index were carried out based on a control group comprised of children who never received the Foster Care Grant in the four time period. This comparison group is conveniently named Control Group 2 for ease of reference. The Treatment Group is comprised of children whose caregivers received the grant twice in the four time period. As highlighted earlier on, the choice of this treatment group is motivated by specifications in the regulation of the grant in which it is categorically stated that the grant is usually for two years with a provision for extension subject to assessment by a social worker given compelling circumstances.

Table 2.14: The Average Treatment Effect on the Treated (ATT) of the Foster Care Grant on Child Health Using Propensity Score Matching (Based on Control Group 2)

	Full Sample (Children aged 0-14 years)	*Sample of Children aged 1-4 years*	*Sample of Children aged 5- 9 years*	*Sample of Children aged 10-14 years*
Height-for-age				
IPTW Matching	-0.225***	-0.665***	-0.285***	-0.135
Nearest Neighbour	-0.203***	-0.874***	-0.219**	-0.132
Weight-for-age				
IPTW Matching	-0.164	-0.455	-0.133	
Nearest Neighbour	-0.164	-0.400	-0.151	
Body Mass Index				
IPTW Matching	-0.153**	-0.366	-0.144	-0.105
Nearest neighbour	-0.159**	-0.404	-0.150	-0.079
Balancing property satisfied	Yes	Yes	Yes	Yes
Common support imposed	Yes	Yes	Yes	Yes
Observations				
Treated	504	57	201	241
Comparison	42623	11648	14257	13466

Notes: Control Group 2 is comprised of children who never received the Foster Care Grant in the four time periods. The Treatment Group is comprised of children who received the Foster Care Grant twice in the four time periods.

Table 2.14 above presents Average Treatment on the Treated Effect (ATT) estimations of the Foster Care Grant on child health using propensity score matching based on Control Group 2. The program has a positive and significant impact on height-for-age for children aged 0-14 years, 1-4 years, and 5-9 years. The estimates are significant at 1 percent. The program improves height-for-age z-score by 0.225, 0.665, and 0.285 standard deviations for the age categories, respectively. These results confirm hypothesis 2.1 above. However, there is no effect for children aged

10-14 years. This, in a way, can be argued to be contrary to the literature of catching up (see Hirvoneni, 2014; Lundeen et al., 2014). The Foster Care Grant, therefore, has a significant impact on height-for-age for children when they are most vulnerable.

The program has no impact on weight-for-age. This result is similar to the result obtained in assessing program intensity above. This means that the program has no impact on short-term changes in nutritional status but rather appeals to the long-term human capital development. As for body mass index, there is no impact for children aged 1-4 years, aged 5-9 years, and aged 10-14 years. A significant result registered for the full sample can therefore be argued to be driven by the 0-1 year olds.

Disaggregating the sample by gender as presented in Table 2.15, the grant has a positive and significant impact on height-for-age for girls. Girls aged 0-14 years who received the Foster Care Grant twice witness an improvement in height-for-age z-scores by 0.226 standard deviations compared to those who did not receive at all. The estimates for girls aged 1-4 years and 5-9 years are positive and significant. However, the program does not have an impact on height-for-age for girls aged 10-14 years. On the other hand, as detailed in Table 2.16, the program has a positive and significant effect on height-for-age for boys aged 0-14 years (full sample) and boys aged 1-4 years with increases in standard deviations by 0.25 and 0.67 respectively. However, there is no impact for boys aged 5-9 years and the estimate for boys aged 10-14 years is weakly significant. Just as in the ATT results on program intensity, the program has a positive and significant impact on weight-for-age for boys aged 1-4 years, increasing the z-score by 0.85 standard deviations. There is no impact on body mass index for boys of all age categories.

Table 2.15: The Average Treatment Effect on the Treated (ATT) of the Foster Care Grant on Girls' Health Using Propensity Score Matching (Based on Control Group 2)

	Full Sample (Children aged 0-14 years)	*Sample of Children aged 1-4 years*	*Sample of Children aged 5-9 years*	*Sample of Children aged 10-14 years*
Height-for-age				
IPTW Matching	-0.226***	-0.689*	-0.362**	-0.075
Nearest Neighbour	-0.212**	-1.111***	-0.350**	-0.014
Weight-for-age				
IPTW matching	-0.156	-0.193	-0.159	
Nearest Neighbour	-0.132	-0.025	-0.278*	
Outcome: Body Mass Index				
IPTW matching	-0.200**	-0.508	-0.216	-0.110
Nearest neighbour	-0.160	-0.483	-0.236	-0.036
Balancing property satisfied	Yes	Yes	Yes	Yes
Common support imposed	Yes	Yes	Yes	Yes
Observations				
Treated	293	36	113	141
Comparison	21028	5853	7047	6694

Notes: Control Group 2 is comprised of children who never received the Foster Care Grant in the four time periods. The treatment Group is comprised of children who received the Foster Care Grant twice in the four time periods.

Table 2.16: The Average Treatment on the Treated Effect (ATT) of the Foster Care Grant on Boys' Health Using Propensity Score Matching (Based on Control Group 2)

	Full Sample (Children aged 0-14 years)	*Sample of Children aged 1-4 years*	*Sample of Children aged 5- 9 years*	*Sample of Children aged 10-14 years*
Height-for-age				
IPTW Matching	-0.250***	-0.674**	-0.201	-0.266*
Nearest Neighbour	-0.259**	-0.371	-0.150	-0.229
Weight-for-age				
IPTW Matching	-0.179	-0.845**	-0.103	
Nearest Neighbour	-0.113	-1.202***	0.003	
Body Mass Index				
IPTW Matching	-0.111	-0.148	-0.038	-0.157
Nearest Neighbour	-0.187	-0.008	-0.030	-0.211
Balancing property satisfied	Yes	Yes	Yes	Yes
Common support imposed	Yes	Yes	Yes	Yes
Observations				
Treated	211	21	88	100
Comparison	21062	5789	7203	6758

Notes: Control Group 2 is comprised of children who never received the Foster Care Grant in the four time periods. The treatment Group is comprised of children who received the Foster Care Grant twice in the four time periods.

Estimation results of the impact of the Foster Care Grant on child health therefore show that the program has a significant impact on height-for-age for children living in South Africa. However, the impact of the program does not cascade to children aged 10-14 years in general. This result is also confirmed in the estimations of the impact of the program intensity above where there is a positive and significant impact on height-for-age for children aged 0-14 years, 1-4 years, and 5-9 years but not significant for children aged 10-14 years. On the other hand, there is a positive and significant impact on height-for-age for both girls and boys. However, as noted above, although there is an impact on height-for-age for girls who received the grant twice as compared to those that do not receive, there is no program intensity impact for girls meaning that there is no further marginal impact for girls who receive the grant twice compared to those that receive it only once. This is an important result. In contrast, however, boys witness both significant program and program intensity impacts. There is no impact on weight-for-age for the full sample and all ages. This result is also confirmed in the program intensity estimations.

2.7.2 Hybrid and Correlated Random-Effects Estimation Results

Results of the Hybrid and Correlated Random-Effects models are detailed in Tables 2.17 to 2.25 and are based on Wave 3(2012), Wave 4(2015), and Wave 5(2017) datasets. Colum (1) details estimation results of the Hybrid model and Column (2) displays Correlated Random-Effects estimations. From the tables, the W-prefix in some variables means within-cluster effects, B_ prefix denotes between-cluster effects, and variables with the R_ prefix are estimated the same way as in standard Random Effects models. Uniquely, variables with a D_ prefix give the difference between the between- and within-cluster effects.

Table 2.17 details estimation results of Hybrid and Correlated Random-Effects models for the full sample (children aged 0-14 years). The variable of interest is binary equaling one if a child received the Foster care Grant and the dependent variable is height-for-age. Receiving the Foster Care Grant is associated with a within-cluster improvement in height-for-age for children aged 0-14 years by 0.06 standard deviations (Table 2.17, Column 1). Within-cluster increases in age are associated with a within-cluster increase in height-for-age by 0.04 standard deviations; an estimate which is significant at 10 percent. However, between-cluster effect of the Foster Care Grant is associated with a between-cluster decrease in height-for-age z-scores by 0.11 standard deviations, albeit weakly significant. An increase in within-cluster household size by one member reduces height-for-age z-

Table 2.17: Hybrid and Correlated Random-Effects Health Estimations for Children aged 0 – 14 years

Dependent Variable = Height-for-age z-score	(1) Hybrid model	(2) Correlated random-effects model
R__Child is female	0.12***	0.12***
	(0.02)	(0.02)
R__Child is Black	0.17***	0.17***
	(0.03)	(0.03)
W__Foster Care Grant	0.06	0.06
	(0.07)	(0.07)
W__Household Size	-0.01	-0.01
	(0.00)	(0.00)
W__Household Head's Education	-0.00	-0.00
	(0.00)	(0.00)
W__Child's age	0.04*	0.04*
	(0.03)	(0.03)
W_ Birth place:Hospital	0.02	0.02
	(0.04)	(0.04)
W__Health-Excellent	-0.01	-0.01
	(0.02)	(0.02)
W__Child has health card	-0.13***	-0.13***
	(0.04)	(0.04)
W__Child has medical aid	-0.10	-0.10
	(0.08)	(0.08)
W__Urban_formal	-0.08	-0.08
	(0.09)	(0.09)
W__Tribal Authority Area	0.08	0.08
	(0.09)	(0.09)
W__Urban_informal	0.07	0.07
	(0.12)	(0.12)
W__Log_income	0.00	0.00
	(0.02)	(0.02)
W__Log_food Expenditure	0.02	0.02
	(0.02)	(0.02)
W__Household Head is female	0.01	0.01
	(0.02)	(0.02)
W__2015 Year Dummy	0.07	0.07
	(0.07)	(0.07)
W__2017 Year Dummy	0.10	0.10
	(0.12)	(0.12)
B__Foster Care Grant	-0.11*	
	(0.06)	
B__Household Size	-0.03***	
	(0.00)	
B__Household Head's Education	0.01***	
	(0.00)	

B__Child’s age	0.01***	
	(0.00)	
B__Birth place hospital	0.05	
	(0.03)	
B__Child’’s health_excellent	0.09***	
	(0.02)	
B__Child has health card	-0.00	
	(0.05)	
B__Child has medical aid	0.28***	
	(0.08)	
B__Urban_formal	0.09**	
	(0.04)	
B__Tribal Authority Areas	0.12***	
	(0.04)	
B__Urban_informal	0.01	
	(0.05)	
B__Log_income	0.06***	
	(0.02)	
B__Log_food expenditure	0.12***	
	(0.03)	
B__Household Head is female	-0.02	
	(0.02)	
B__2015 Year dummy	0.19***	
	(0.04)	
B__2017 Year dummy	0.12***	
	(0.04)	
D__Foster Care Grant		-0.18**
		(0.09)
D__Household Size		-0.02***
		(0.01)
D__Household Head’s Education		0.02***
		(0.00)
D__Child’s age		-0.03
		(0.03)
D__Birth place: hospital		0.03
		(0.05)
D__Child’s health: excellent		0.10***
		(0.03)
D__Child has health card		0.12*
		(0.07)
D__Child has medical aid		0.39***
		(0.12)
D__Urban_formal		0.17*
		(0.10)
D__Tribal Authority Areas		0.04
		(0.10)
D__Urban_informal		-0.06
		(0.13)
D__Log_income		0.05**
		(0.03)

D__Log_food expenditure		0.10***
		(0.03)
D__Household Head is female		-0.03
		(0.03)
D__2015 year dummy		0.11
		(0.08)
D__2017 year dummy		0.02
		(0.13)
Constant	-2.71***	-2.71***
	(0.17)	(0.17)
Observations	25,554	25,554
Number of groups	14,903	14,903

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Dependent Variable is height-for-age z-score. B_ prefix means between-cluster effects; D_ gives the differences between the between- and within-cluster effects; and R_ prefix denote same effects as those in standard random-effects model.

scores for children by 0.03 standard deviations and is significant at 1 percent. The between-cluster effects of household head's education, child's age, child's health, whether a child has a medical aid, a child lives in Tribal Authority Areas compared to those that live in the rural areas, log of household income, log of food expenditure, 2015 year dummy, and 2017 year dummy are all positive and significant at 1 percent.

The estimations and test results not included in the appendix, proved that the within-cluster effects are statistically different from the between-cluster effects as evidenced by small p-values obtained in the tests of orthogonality between observables and unobservables. This is applicable to all variables except for the child's age, birthplace at a hospital, geographical areas (informal urban area and tribal authority area), female household headship, and year dummies. All the same it is evidence enough to reject the assumption of orthogonality and therefore ground for not using the Random Effects model.

Column (2) of Table 2.17 details Correlated Random-Effects estimation results of the effect of the Foster Care Grant on height-for-age. There is a positive within-group effect for children receiving the Foster Care Grant. Having a health card compared to not having one is associated with a within-cluster decrease in height-for-age z-score by 0.13 standard deviations, which is significant at 1 percent. The Correlated Random-Effects estimations show that the difference between the between- and the within-cluster effects of the Foster Care Grant on height-for-age is negative by a factor of 0.18 which is significant at 5 percent. The differences for household head's education, child's health, child has a medical aid, lives in formal urban area, log of household income, and log of food expenditure are all positive and significant.

Table 2.18 below details Hybrid and Correlated Random-Effects estimation results of the effect of the Foster Care Grant on height-for-age for children aged 1-4 years. Both the Hybrid and Correlated Random–Effects models predict that receiving the Foster Care Grant leads to a within-cluster effect of 0.58 standard deviations in height-for-age, which is significant at 10 percent. It is worth mentioning in passing that within-cluster increases in household size are associated with a within-cluster decrease in height-for-age z-scores and increases in a child's age is associated with a within-cluster increases in height-for-age z-scores by 0.33 standard deviations and are both strongly statistically different from zero.

Table 2.18: Hybrid and Correlated Random-Effects Estimations for Children aged 1 – 4 years

Dependent Variable = Height-for-age z-score	(1) Hybrid model	(2) Correlated random-effects model
W__Foster Care Grant	0.58*	0.58*
	(0.32)	(0.32)
W__Household Size	-0.04**	-0.04**
	(0.02)	(0.02)
W__Household head's education	-0.00	-0.00
	(0.02)	(0.02)
W__Household head's age	0.00	0.00
	(0.00)	(0.00)
W__Child's age	0.33***	0.33***
	(0.10)	(0.10)
W__Child is female	-0.16	-0.16
	(0.59)	(0.59)
W__Black	0.02	0.02
	(0.90)	(0.90)
W__Birth place – hospital	0.05	0.05
	(0.13)	(0.13)
W__Child's health: excellent	0.01	0.01
	(0.07)	(0.07)
W__Child has health card	0.04	0.04
	(0.24)	(0.24)

W__Child has medical aid	-0.29	-0.29
	(0.32)	(0.32)
W__Urban_formal	-0.27	-0.27
	(0.30)	(0.30)
W__Tribal Authority Areas	-0.29	-0.29
	(0.30)	(0.30)
W__Urban_informal	0.08	0.08
	(0.40)	(0.40)
W__Log_income	0.11*	0.11*
	(0.06)	(0.06)
W__Log_food expenditure	-0.03	-0.03
	(0.07)	(0.07)
W__Household head is female	-0.06	-0.06
	(0.09)	(0.09)
W__2015 year dummy	-0.48*	-0.48*
	(0.26)	(0.26)
W__2017 year dummy	-0.83*	-0.83*
	(0.47)	(0.47)
B__Foster Care Grant	-0.01	
	(0.18)	
B__Household Size	-0.04***	
	(0.01)	
B__Household head's education	0.03***	
	(0.01)	
B__Household head's age	0.01***	
	(0.00)	
B__Child's age	0.08***	
	(0.02)	
B__Child is female	0.14***	
	(0.04)	
B__Black	0.17***	
	(0.06)	
B__Birth place - hospital	0.04	
	(0.05)	
B__Child's health: excellent	0.07*	
	(0.04)	
B__Child has health card	-0.02	
	(0.15)	
B__Child has medical aid	0.07	
	(0.14)	
B__Urban_formal	0.04	
	(0.07)	
B__Tribal Authority Areas	0.14**	
	(0.07)	
B__Urban_informal	-0.05	
	(0.09)	
B__Log_income	0.08**	
	(0.03)	
B__Log_food expenditure	0.08*	
	(0.04)	

B__Household head is female	0.00	
	(0.04)	
B__2015 year dummy	-0.01	
	(0.05)	
B__2017 year dummy	-0.04	
	(0.05)	
D__Foster Care Grant		-0.59
		(0.37)
D__Household Size		0.00
		(0.02)
D__Household head's education		0.03
		(0.02)
D__Household head's age		0.00
		(0.00)
D__Child's age		-0.25**
		(0.10)
D__Child is female		0.31
		(0.59)
D__Black		0.16
		(0.90)
D__Birth place - hospital		-0.01
		(0.14)
D__Child's health: excellent		0.06
		(0.08)
D__Child has health card		-0.06
		(0.28)
D__Child has medical aid		0.36
		(0.35)
D__Urban_formal		0.32
		(0.31)
D__Tribal Authority Areas		0.43
		(0.31)
D__Urban_informal		-0.13
		(0.42)
D__Log_income		-0.03
		(0.07)
D__Log_food expenditure		0.10
		(0.08)
D__Household head is female		0.06
		(0.10)
D__2015 year dummy		0.48*
		(0.26)
D__2017 year dummy		0.79*
		(0.47)
Constant	-3.18***	-3.18***
	(0.32)	(0.32)
Observations	6,856	6,856
Number of groups	5,712	5,712

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Dependent Variable is height-for-age z-score. B_ prefix means between-cluster effects; D_ gives the differences between the between- and within-cluster effects; and R_ prefix denote same effects as those in standard random-effects model.

For children aged 5-9 years, the within-cluster effect of the Foster Care Grant is positive but not significant. These results are detailed in Table 2.19.

Table 2.19: Hybrid and Correlated Random-Effects Estimations for Children aged 5-9 years

Dependent Variable = Height-for-age z-score	(1) Hybrid model	(2) Correlated random-effects model
R__Black	0.18***	0.18***
	(0.05)	(0.05)
W__Foster Care Grant	0.12	0.12
	(0.11)	(0.11)
W__Household Size	-0.00	-0.00
	(0.01)	(0.01)
W__Household head's education	-0.00	-0.00
	(0.01)	(0.01)
W__Child's age	0.09**	0.09**
	(0.04)	(0.04)
W__Child is female	-0.07	-0.07
	(0.27)	(0.27)
W__Birth place -hospital	0.09	0.09
	(0.08)	(0.08)
W__Child's health: excellent	-0.04	-0.04
	(0.03)	(0.03)
W__Child has health card	-0.00	-0.00
	(0.08)	(0.08)
W__Child has medical aid	0.00	0.00
	(0.13)	(0.13)
W__Urban_formal	-0.01	-0.01
	(0.16)	(0.16)
W__Tribal Authority Areas	0.18	0.18
	(0.16)	(0.16)
W__Urban_informal	0.04	0.04
	(0.20)	(0.20)
W__Log_income	0.01	0.01
	(0.03)	(0.03)
W__Log_food expenditure	0.05	0.05
	(0.03)	(0.03)
W__Household head is female	-0.02	-0.02
	(0.04)	(0.04)
W__2015 year dummy	-0.08	-0.08
	(0.11)	(0.11)

W__2017 year dummy	-0.17	-0.17
	(0.19)	(0.19)
B__Foster Care Grant	-0.10	
	(0.09)	
B__Household Size	-0.03***	
	(0.00)	
B__Household head's education	0.01**	
	(0.00)	
B__Child's age	0.03**	
	(0.01)	
B__Child is female	0.05*	
	(0.03)	
B__Birth place -hospital	0.05	
	(0.04)	
B__Child's health: excellent	0.06**	
	(0.03)	
B__Child has health card	-0.03	
	(0.07)	
B__Child has medical aid	0.28***	
	(0.10)	
B__Urban_formal	0.19***	
	(0.05)	
B__Tribal Authority Areas	0.22***	
	(0.05)	
B__Urban_informal	0.17**	
	(0.07)	
B__Log_income	0.04	
	(0.02)	
B__Log_food expenditure	0.09***	
	(0.03)	
B__Household head is female	-0.04	
	(0.03)	
B__2015 year dummy	0.11**	
	(0.04)	
B__2017 year dummy	0.12***	
	(0.04)	
D__Foster Care Grant		-0.21
		(0.14)
D__Household Size		-0.02**
		(0.01)
D__Household head's education		0.01*
		(0.01)
D__Child's age		-0.07
		(0.04)
D__Child is female		0.13
		(0.27)
D__Birth place - hospital		-0.04
		(0.08)
D__Child health: excellent		0.11***
		(0.04)

D__Child has health card		-0.03
		(0.11)
D__Child has medical aid		0.28*
		(0.16)
D__Urban_formal		0.19
		(0.16)
D__Tribal Authority Areas		0.04
		(0.17)
D__Urban_informal		0.12
		(0.21)
D__Log_income		0.03
		(0.04)
D__Log_food expenditure		0.04
		(0.05)
D__Household head is female		-0.02
		(0.05)
D__2015 year dummy		0.18
		(0.11)
D__2017 year dummy		0.29
		(0.20)
Constant	-2.23***	-2.23***
	(0.24)	(0.24)
Observations	9,579	9,579
Number of groups	7,096	7,096

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Dependent Variable is height-for-age z-score. B_ prefix means between-cluster effects; D_ gives the differences between the between- and within-cluster effects; and R_ prefix denote same effects as those in standard random-effects model.

On the other hand, Table 2.20 details the Hybrid and Correlated Random-Effects estimation results of the effect of the Foster Care Grant on height-for-age for children aged 10-14 years. Receiving the Foster Care Grant by children aged 10-14 years is associated with a within-cluster increase in height-for-age by 0.16 standard deviations, which is significant at 10 percent. However, the between-cluster effect of the Foster Care Grant on height-for-age for children aged 10-14 years is negative and weakly significant with a factor of 0.11. The difference between the between- and within-cluster effect of the Foster Care Grant on height-for-age is significant at 5 percent with a factor of 0.27 standard deviations, though negative.

Table 2.20: Hybrid and Correlated Random-Effects Estimations for Children aged 10-14 years

Dependent Variable = Height-for-age z-score	(1) Hybrid model	(2) Correlated random-effects model
R__Child is female	0.13***	0.13***
	(0.03)	(0.03)
R__Black	0.13***	0.13***
	(0.05)	(0.05)
W__Foster Care Grant	0.16*	0.16*
	(0.09)	(0.09)
W__Household Size	0.01	0.01
	(0.01)	(0.01)
W__Household Head's Education	-0.00	-0.00
	(0.01)	(0.01)
W__Child's age	-0.01	-0.01
	(0.04)	(0.04)
W__Birth place – hospital	0.03	0.03
	(0.07)	(0.07)
W__Child's health: excellent	0.06**	0.06**
	(0.03)	(0.03)
W__Child has health card	-0.12**	-0.12**
	(0.05)	(0.05)
W__Child has medical aid	-0.21	-0.21
	(0.14)	(0.14)
W__Urban_formal	-0.06	-0.06
	(0.15)	(0.15)
W__Tribal Authority Areas	-0.00	-0.00
	(0.16)	(0.16)
W__Urban_informal	0.05	0.05
	(0.20)	(0.20)
W__Log_income	0.01	0.01
	(0.03)	(0.03)
W__Log_food expenditure	-0.00	-0.00
	(0.03)	(0.03)
W__Household Head is female	-0.04	-0.04
	(0.04)	(0.04)
W__2015 year dummy	0.15	0.15
	(0.10)	(0.10)
W__2017 year dummy	0.09	0.09
	(0.19)	(0.19)
B__Foster Care Grant	-0.11*	
	(0.06)	
B__Household Size	-0.02***	
	(0.00)	
B__Household Head's Education	0.02***	
	(0.00)	

B__Child’s age	-0.08***	
	(0.01)	
B__Birth place – hospital	0.06*	
	(0.04)	
B__Child’s health: excellent	0.05	
	(0.03)	
B__Child has health card	-0.13**	
	(0.05)	
B__Child has medical aid	0.24*	
	(0.13)	
B__Urban_formal	0.05	
	(0.05)	
B__Tribal Authority Areas	0.03	
	(0.05)	
B__Urban_informal	-0.01	
	(0.07)	
B__Log_income	0.00	
	(0.03)	
B__Log_food expenditure	0.11***	
	(0.03)	
B__Household Head is female	-0.02	
	(0.03)	
B__2015 year dummy	0.33***	
	(0.04)	
B__2017 year dummy	0.35***	
	(0.04)	
D__Foster Care Grant		-0.27**
		(0.11)
D__Household Size		-0.03***
		(0.01)
D__Household head’s Education		0.02***
		(0.01)
D__Child’s age		-0.07*
		(0.04)
D__Birth place – hospital		0.03
		(0.08)
D__Child’s health: excellent		-0.02
		(0.04)
D__Child has health card		-0.01
		(0.08)
D__Child has medical_aid		0.45**
		(0.19)
D__Urban_formal		0.11
		(0.16)
D__Tribal Authority Areas		0.03
		(0.17)
D__Urban_informal		-0.06
		(0.21)
D__Log_income		-0.00
		(0.04)

D__Log_food expenditure		0.11**
		(0.05)
D__Household Head is female		0.02
		(0.05)
D__2015 year dummy		0.18
		(0.11)
D__2017 year dummy		0.26
		(0.19)
Constant	-1.20***	-1.20***
	(0.27)	(0.27)
Observations	8,456	8,456
Number of groups	6,290	6,290

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Dependent Variable is height-for-age z-score. B_ prefix means between-cluster effects; D_ gives the differences between the between- and within-cluster effects; and R_ prefix denote same effects as those in standard random-effects model.

2.8 Discussion

It is important to comment on the findings of the impact of the Foster Care Grant on height-for-age vis-a-vis the impact of the grant on weight-for-age. One would expect short-run effects on height to be small. In this study, compared to estimates on weight-for-age, the estimates on height-for-age are relatively larger. However, the results are acceptable considering that in general, the estimates on weight-for-age are not statistically different from zero. On the other hand, it is not entirely unique to witness a situation where estimates on the impact of a program on height-for-age are relatively larger than those for weight-for-age. For example, for the Targeted Resource Transfers for families program in Nepal, Renzaho et al. (2017) obtained relatively greater improvement in height-for-age for children compared to the improvement in weight-for-age after a five-year period of intervention.

Furthermore, the estimates on the impact of the Foster Care Grant on height-for-age compare very well with estimates of cash transfers in South Africa. For example, Duflo (2003) discovered that girls living with a member eligible for the Old Age Pension program experience an increase in height-for-age by 0.68 standard deviations and 0.11 for boys; and also discovered that pensions received by women improved the height-for-age z-scores of younger girls by at least 1.16 standard deviations. On the other hand, the Child Support Grant in South Africa was observed to increase children under the age of 36 months' height-for-age z-scores by 0.25

standard deviations (see e.g. de Groot et al., 2015). Elsewhere, the effect of the *Samurdhi* in Sri Lanka on height-for-age for children under five years ranges between 0.4 and 0.5 standard deviations (ibid.). The Apni Beti Apna Dhan program in India improved child height by over 0.3 standard deviations (Manley et al., 2013). It is also important to note that program characteristics play a role in influencing impact, some of which are, among others, payment size and duration. As noted in section 2.2 above, the Foster Care Grant is relatively generous.

It is not directly possible to determine from the data children who were fostered but did not receive the Foster Care Grant. This may be viewed as a limitation in that there may be arguments for using just a sample of fostered children in assessing the impact of the grant. However, given the empirical strategy adopted in this study, it is plausible to argue that this limitation can be ignored. Propensity Score Matching is capable of appropriately assigning observations into treatment and control groups based on observables. On the other hand, just using the sample of fostered children may accentuate the problem of selection bias that the Propensity Score Matching is not able to fully address if the bias emanates from unobserved characteristics. If foster parents who chose to apply for the Foster Care Grant are systematically different from foster parents who choose not to apply for the grant and these characteristics are unobserved, then selection bias will be greater. Related, just choosing a sample of fostered children may suffer from sample selection bias. It can therefore be argued that broadening the sample may reduce this bias especially considering that the Propensity Score Matching adopted in this study does not address the challenge when the characteristics are unobserved. It is proposed, however, that further research can focus on evaluating how the Foster Care Grant affects outcomes for unfostered children living in the same household.

The presence of bias emanating from unobserved characteristics can explain the difference in the impact size estimates between the Propensity Score Matching and the Correlated Random Effects (as well as those from the Hybrid Model). Program impact estimates from the Hybrid and the Correlated Random Effects models are relatively smaller when compared to estimates obtained using Propensity Score Matching. This confirms that whatever the unobserved heterogeneity bias that may have persisted in the estimates obtained through Propensity Score Matching must have been sufficiently dealt with under the Hybrid and Correlated Random Effects models.

It is also important to comment on the importance of disaggregating the sample according to different age groups and gender. One of the strengths of this study is the quality of the data. This study draws from a huge panel data with five waves as detailed in Table 2.1 in Section 2.4. This allowed the disaggregation of the sample into sub-groups which, enriched the analysis and allowed further interrogation of the issue at stake. When assessing the impact of a cash transfer on child health outcomes, it is more informative to disaggregate the sample based on age groups. Studies on health outcomes are encouraged to stratify their analyses by appropriate age brackets (see e.g. Alderman and Headey, 2018). It is generally accepted that children younger than two years are more vulnerable to poor diets (see e.g. Leroy et al., 2015) and there is continued widening of the absolute height deficit for children between two to five years. Therefore, disaggregating the sample into age brackets enhances understanding of the impact of the Foster Care Grant on child health which is essential on informing the targeting of interventions.

Prior works on cash transfers in South Africa have indicated gender heterogeneity to impact of cash transfers on child health. Duflo (2003), for example, concluded that the expansion of the Old-age Pension program in South Africa led to an improvement in the health and nutrition of girls and no discernible effect on boys. It is therefore important to disaggregate the sample according to gender so as to be able to determine the effect of the Foster Care Grant on boys vis-a-vis on girls. In tests separately carried out, the results indicate that the coefficients are significantly different from each other, confirming the existence of heterogeneity across the sub-groups. In one of the tests, I used the Wald chi-square test after estimating separate models for boys and girls after which I then used *suest* to combine the models and tested whether the coefficients differ across the groups. In each case the groups are significantly different from each other. I also compared the 95 percent confidence intervals between the groups and I discovered that they do not overlap, meaning that there are statistically significant differences at 5 percent level.

In future, should there be a major policy shift in the way the Foster Care Grant is administered or should there be an exogenous shock affecting eligibility for the grant, then other empirical strategies such as the Difference-in-Differences framework may be adopted to check the robustness of the findings presented in this study. A shift in policy that makes a certain group of people that are not currently eligible for the grant to become suddenly eligible will present a natural experiment in which a double difference between 'treatment and control group before and after the policy change' would show the impact of the Foster Care Grant on a number of selected outcomes. Such a policy shift may also allow empirical strategies such as the Regression Discontinuity Design to establish the impact of the Foster Care Grant in the neighbourhood of those that find themselves suddenly eligible against those that narrowly become ineligible.

2.9 Conclusion

The Foster Care Grant in South Africa is an unconditional social protection program intended to provide for the basic needs of children who have been placed in the care of foster parents by a Children's Court. The grant is generous and presents an interesting case study, which has not been subjected to rigorous evaluations and has not received much attention. The study bridged this gap by assessing its impact on height-for-age, weight-for-age, and body mass index.

The findings indicate that the program has a positive and significant impact on height-for-age for the full sample (children aged 0-14 years), for children aged 1-4 years, and for children aged 5-9 years. However, the impact does not cascade to children aged 10-14 years, a result running contrary to studies on catching up such as Rieger and Wagner (2015). The results also show a positive and significant program intensity impact for boys on height-for-age. To the contrary, there is no such further marginal impact for girls who receive the grant twice compared to those that receive it only once. This result seems to be at parallel with findings by Manley et al. (2013) and Duflo (2003) where they discovered that girls tend to benefit more than boys. Since there is a provision for extension to access the Foster Care Grant after the initial two years, it can therefore be encouraged, where circumstances allow, that boys be allowed to access the grant more than once since it leads to program intensity impacts.

The findings also indicate that in general, there is no program intensity and program impact on weight-for-age. This means that the program has no impact on short-term changes in nutritional status but rather appeals to the long term human capital development through height-for-age. The Foster Care Grant has an impact on height-for-age. This result runs contrary to studies such as Kirk et al. (2018)'s findings elsewhere in Africa who find no impact of unconditional cash transfers on height-for-age. The grant, therefore, has a significant impact on height-for-age for foster children in South Africa.

CHAPTER 3

COPING STRATEGIES, AGRICULTURAL EXTENSION SERVICES AND THE IMPACT OF SOCIAL CAPITAL ON FOOD SECURITY IN ZIMBABWE

3.1 Introduction

Food security is a perennial challenge for many households in Zimbabwe. This is as a result of a number of factors ranging from droughts, climate change (see e.g. Govere et al., 2020; Hove and Gweme, 2018; Nyagumbo et al., 2019) to land tenure. For example, some parts of Zimbabwe have become synonymous with drought (Belle, 2017; Mavhura, 2017) and flood-related disasters (Gwimbi, 2007) which destroy crops, livestock and hopes resulting in food insecurity. The creation of small to medium land holdings from what used to be large scale commercial farms has created heterogeneity in productivity (see e.g. Moyo and Salawu, 2018) and contributing to persistent poverty and food insecurity among smallholder farming households (see e.g. Komarek et al., 2017; Ragasa and Mazunda; 2018). Coupled with lack of appropriate agricultural technologies and little research and development, this has left many households at the mercy of food insecurity.

When faced with food insecurity, households tend to rely on social protection programs (Bhalla et al., 2018) such as cash transfers. However, in the absence of formal programs, households fall back on their social networks and other coping strategies to ensure that they survive (see e.g. Fafchamps, 2006; Fafchamps and Lund, 2003). Social capital may enhance the ability of households, villages and communities to tap from informal social support among neighbours and group members that might curb food insecurity.

Households and minority groups with low social capital experience food insecurity (Dean and Sharkey, 2011). Relatedly, community-level social capital is also significantly associated with decreased odds of experiencing hunger (Martin et al., 2004). On the other hand, individual and collective behaviour, social networks, and associations have a great influence on responses and recovery systems against shocks (see e.g. Chan et al., 2018; Kerr, 2018; Nagoli and Chiwon-Karltun, 2017; Pacoma and Delda, 2019; Paul et al., 2019; Sabatino, 2019). Collective action necessitates pooling of resources, knowledge, and effort for community responses (see e.g Bourne et al., 2017).

It is generally accepted that social capital is contextual (Ehsan et al., 2019; MacGillivray, 2018). This is the reason why, in each specific context, social capital remains an interesting research area. Alternative measures may only be relevant to particular levels – individual, household and community – of social capital (Paul et al., 2019). It is important to consider different measures in different contexts and this study adds to the literature by presenting results of the impact of social capital on food security in Zimbabwe. As noted by Sabatino (2019), there is still absolute necessity to consider the different social capital measures and this research does so by using ‘belonging to a social group’ as a measure of social capital.

In Zimbabwe, social groups are increasingly becoming important given the collapse of formal institutions and persistent poverty. Households are forced to resort to their social networks for resources and information. Belonging to a social group can therefore be viewed as a potential resource for household food security. This explains why social capital measured as ‘belonging to a social group’ is important in the context of Zimbabwe. Specifically, this study seeks to answer the following questions. First, are households with members belonging to a social group more likely to be food-secure and less likely to go hungry than those without? When faced with food insecurity, households tend to adopt and adapt to certain behavioural hunger-coping strategies. So, second, are households with members belonging to social groups less likely to adopt behavioural hunger-coping strategies? Third, does social capital increase the likelihood of a household receiving and seeking agricultural extension services? Finally, does social capital increase the likelihood of a household treating its harvest against post-harvest losses?

To answer these questions, this research uses a nationally representative dataset collected annually by the Zimbabwe Vulnerability Assessment Committee (ZIMVAC), which is a consortium of the Government of Zimbabwe, Development Partners, United Nations, NGOs, and Technical Agencies. For the purpose of this study, 2015 ZIMVAC cross-sectional data was selected specifically because it is the only survey that asked whether households had members belonging to a social group. Other later surveys used trust as a measure of social capital, which was not of interest in this study. A quasi-experimental method, Propensity Score Matching, was used to ascertain the effect of social capital.

The study offers the following major findings. First, households with members belonging to a social group are more food secure and are less likely to go hungry than those without membership. Social capital ensures food security and decreases the risk of hunger in Zimbabwe. Second, households with members belonging to a social group are less likely to engage in demanding and psychologically stressful food insecurity coping strategies such as skipping meals, limiting portion size of meals and reducing number of meals eaten. Third, households with members belonging to a social group are more likely to participate in agricultural training; receive visits from agricultural extension officers, seek cropping and veterinary advice, and technical support. Finally, households with members belonging to a social group are more likely to treat their harvest against post-harvest losses. This ensures food security.

The rest of the Chapter proceeds as follows. The next section reviews relevant literature and outlines the hypotheses to be tested. Section 3.3 describes the data used in this research and offers descriptive statistics and Section 3.4 details the design of the study, while Section 3.5 presents the results and Section 3.6 concludes.

3.2 Literature Review

This section presents a discussion on theoretical framework and empirical review including a detailed consideration and discussion on the concept of social capital in general and on household hunger and food security, coping strategies, and agricultural extension services in particular.

3.2.1 Social Capital, household hunger and food security

The literature generally acknowledges that the concept of social capital is 'definition-elusive', debatable, multi-layered and complex (Ng'ang'a, 2016; Nguyen-Trung et al., 2020; Sabatino, 2019). It embodies features of social organization such as trust, norms and networks that enhances coordination and cooperation for reciprocal benefit (Putman, 1995). It is also seen as a 'stock' or set of resources in-built in social networks (Lin, 2017; Sabatino, 2019) and therefore viewed as an asset of social norms and networks at the core of community collective actions (Woolcock and Narayan, 2000). Social capital is, in simple terms, frequently defined in terms of trust, adherence to norms or participation in networks (Fedes van Rijn, 2015). It is a resource at the disposal of individuals and households, which emerges from their social bonds and from belonging to a community.

Food security, on the other hand, is important in building a health society. Household food insecurity has been linked to an array of negative psychological outcomes, such as mental distress and accompanying feelings of depression, especially among parents (see Jackson et al., 2019; Mandelbaum et al., 2018) may be because food insecurity is often linked to family-level processes (Jackson and Vaughn, 2017). It may also be linked to neighbourhoods with low social capital, meaning that higher levels of social capital are correlated with decreased risk of household hunger (Nebbitt et al., 2016). A low level of social capital may undermine the ability of a community to tap from informal social support among neighbours and group members that might curb food insecurity. The argument is that social networks in highly cohesive communities can act as a fall-back when families in the community face hunger.

It can, therefore, be argued that belonging to a social group can be a potential resource for household food security. This is because social groups provide a channel through which households gain new information, resources, and opportunities. Being a member creates belonging and a sense of confidence; and members receive acceptance, empathy and support. This leads to the following hypotheses linking social capital to food security and household hunger:

Hypothesis 3.1.1:

Households with members belonging to a social group are more likely to be food-secure than those without membership.

Hypothesis 3.1.2:

Households with members belonging to a social group are less likely to experience a day when there is no food to eat, go to sleep at night hungry, or go a whole day and night hungry.

Low social capital is associated with food insecurity (see e.g. Dean and Sharkey, 2011; Jackson et al., 2019; Johnson et al., 2010). Martin et al. (2004) explored whether social capital is positively associated with decreased risk of hunger and concluded that social capital at both the household and community levels is significantly associated with household food security. According to them, community-level social capital is significantly associated with decreased odds of experiencing hunger. They also found that having a household member who participates in a social or civic organization is also significantly associated with having higher levels of social capital. Social capital, especially in terms of reciprocity among neighbours, according to them, contributes to household food security. Households with higher levels of social capital are less likely to experience hunger.

This research, however, is distinct from theirs on a number of fronts. First, although they focused on the impact of social capital on household food security, social capital is contextual since participation is likely to be influenced by culture. Their study area is a developed country and this research adds to extant literature from a developing country's perspective. Second, the measure of social capital they used is different from the one adopted in this study. In their paper, they used social capital measured using a 7-item Likert scale analysed at household and community level whereas in this study social capital is a binary response indicating whether a household has a member who belongs to a social group. Third, in their empirical strategy, they used a logistic regression and this study adopts a different empirical strategy which is based on quasi-experimental approach.

Although Dean and Sharkey (2011) looked at social capital and food insecurity, this research is distinct in that it focuses on households as opposed to individuals. The argument for them is that access of specific individuals to community-based resources is grounded in these individuals' engagement with their community. A counter argument in this research is that in Zimbabwe, ensuring food security is mainly shouldered by household heads and in turn they make decisions for the household. This view tends to support what Morton et al. (2008) referred to as 'reciprocal economies' where food is shared among friends, family members, neighbors and other community members. Such decisions are usually made by household heads on behalf of the household. An individual level cross-sectional study of social capital and food insecurity may not address social capital as a structural property. Furthermore, their measure of social capital focuses on extra-familial community components such as trust in one's community or community safety.

3.2.2 Social Capital and Coping Strategies

Households and communities, particularly in developing countries, find themselves at the receiving end of shocks and are 'forced' to adopt and adapt coping strategies to get by. Such shocks include but are not limited to climate risk and food insecurity. When faced with food insecurity, households may adopt aggressive coping strategies such as skipping meals, limiting portion size of meals, reducing number of meals eaten, and borrowing food.

Individual and collective behaviour, social networks, and associations have a great influence on responses and recovery systems against shocks. Sabatino (2019) examined the relationship between resilience and social capital and presented a review of the theory on the concepts of resilience and social capital concluding that the relationship between social capital and resilience is important. Interest is on the capacity to resist shocks using a social system of relations between individuals and the ability of social groups and the community to 'adapt, support, absorb, and cope' with shocks such as food insecurity. At community level, coping processes are targeted at supporting and revamping social connections and a sense of belonging and finding common solutions to common problems.

In the face of food insecurity, a resilient household is one that can develop and take steps to strengthen individual and household responsibility to address and manage the change in welfare. The household would respond in relation to pressure from the shock and invoke the necessary structures and resources. This is where social capital is called in to cushion households in the face of adverse shocks. A resistant household with social capital is exposed to stress without suffering serious damage because its social networks respond effectively through cohesion, shared identity, learning and adaptability. This line of reasoning is consistent with the findings by Pacoma and Delda (2019). Their results reveal that local and translocal ties add to household resilience by way of providing food, financial assistance and psychological support.

Nagoli and Chiwona-Karltun, (2017) provide an in-depth understanding on how social dynamics of kinship ties assist in coping with shocks from the recessions of Lake Chilwa in Malawi. In good seasons, Lake Chilwa provides food security to over 1.5 million people through crop husbandry and fishing. In their paper, they interrogated gender roles and relationships at the community level to shed light on how social structures affect coping strategies during lake recessions. They concluded that during lake recessions, poor households fall back on fellow households through lineage networks. Generally, their findings shed light on how households, communities and their livelihoods respond to shocks. However, this research is distinct from Nagoli and Chiwona-Karltun's work in that they looked at community level whereas this research focuses on households.

Much of the work on social capital and coping strategies focuses on climate change (see e.g. Bott et al., 2019; Chan et al., 2018; Mbiba et al., 2019; Ng'ang'a et al., 2016; Paul et al., 2019) and not on immediate household decisions facing food insecurity such as skipping meals, limiting portion size, and reducing number of meals. Few studies have described and assessed potential behavioural coping strategies among the food insecure (see e.g. Hoisington et al., 2002; Pinard et al., 2016). Martin and Lippert (2012) observed that food insecure mothers skip meals, wait to eat until later in the day, or eat less to spare their children from hunger. In a case study of Zvishavane district in Zimbabwe, Ncube et al. (2018) discovered that rural women develop and adopt drought coping strategies such as, among others, skipping meals and reducing meal portions. Harvey (2016), Purdam et al. (2016) and Puddephatt et al. (2020) also observed that the food insecure report restrictive eating patterns such as eating smaller meals, skipping meals and not eating for an entire day.

Behavioural hunger-coping strategies such as skipping meals, limiting portion size of meals and reducing number of meals eaten may result in problems such as insufficient food intake and nutritional imbalance (see e.g. Lee et al., 2019). This may lead to health challenges such as illnesses, mental health problems and generally poor quality of life as well as depressive disorder (Daniel, 2020; Kwak and Kim, 2017; Lee et al., 2017).

Investing in social capital is at the core of strategies that most households rely on in responding to shocks. Adaptive households enable knowledge exchange through social exposure between individuals, households and groups with both homogenous and diverse socio-economic characteristics. Belonging to a social group and investing in social networks is important and effective in the presence of idiosyncratic food insecurity shocks. This is because households with members belonging to socially knit social groups can rely on the informal social protection and insurance through sharing arrangements premised on altruism or expected reciprocity that ensures food security. Social capital, this way, provides a mechanism through which households can protect themselves against shocks and therefore it has an inverse relationship with coping strategies such as skipping meals, limiting portion size of meals, reducing number of meals eaten and borrowing food. Therefore, the following hypothesis linking social capital to household coping strategy is proposed:

Hypothesis 3.2:

Households with members belonging to a social group are less likely to engage in behavioural hunger-coping strategies such as skipping meals, limiting portion size of meals, reducing number of meals and borrowing food.

3.2.3 Social Capital and Agricultural Extension Services

Agricultural extension services provide households and farmers with information, advice and training on various aspects related to agriculture, agricultural productivity and markets. Agricultural advisory systems, agricultural extension and veterinary services refer to the whole array of organisations that support and help people involved in agricultural production to solve problems and to get information, gain skills and obtain technologies to improve livelihoods and welfare. Agricultural extension, advisory and veterinary services therefore ensure food security if the advice is taken to productive use. They ensure food security through unlocking sustainable agricultural productivity and by bridging the gap between research and farmer practices, and aim to enhance livelihoods and well-being of communities, particularly in rural areas, by facilitating information exchange and capacity for collective action (Bourne et al., 2017).

Advisory services are not only concerned with the transfer of technology and knowledge, but also facilitating households and farmers to make collective decisions and cooperate as well as forming effective institutions for managing collective activities. There is knowledge diffusion from researchers to farmers, among farmers and from community to researchers. This way therefore, extension officers and advisory agents strengthen ties between farmers and other actors. Bourne et al. (2017) acknowledges that there has been a transition in approaches used to deliver advisory services from technology transfer only to promoting both information flow and developing capacity for collective action.

Social capital can loosely be viewed as a form of social protection and evidence shows that social protection does not only have positive welfare impacts but also stimulates productive activity among households (Cropensstedt et al., 2018). This is essential particularly in rural areas where most of the poor live and where agriculture remains pivotal to their livelihoods and food security. For them, linking social protection with agricultural development may ensure food security. Cropensstedt et al. (2018) acknowledged that informal support systems are important institutions in most communities and there are potential synergies between informal support mechanisms and formal social protection programmes in enhancing food security, agricultural growth and sustainable rural development. According to them, integrating principles from informal networks into formal programmes is likely to make these more effective and trusted. In the spirit of this line of reasoning, agricultural extension services represent the formal and social capital the informal support systems, which when integrated ensures household food security.

Fédes van Rijn et al. (2015) assessed the impact of agricultural extension services on social capital and found indications that agricultural extension services result in higher levels of intra-village networks (bonding social capital) in Rwanda and improved trust and norms of cooperation (cognitive social capital) in the Democratic Republic of Congo. They observed that agricultural education and extension efforts need to take into consideration the role of social capital in program success emphasising the need to have social capital indicators incorporated in the design and analysis of evaluation tools of agriculture-related development initiatives. However, their study compared to this research clearly shows that agricultural extension services and social capital are endogenous. This research is distinct from theirs in that social capital is the variable of interest and agricultural extension services is the outcome variable whereas the opposite is true in their case.

Relatedly, Bourne et al. (2017) proposed a framework linking social network measures to information flow and capacity for collective action and applied it to networks in 11 sites within East Africa. Their results provide valuable insight into performance of existing advisory systems. However, based on information networks, anecdotal evidence and literature, they found limited capacity for collective action within farmer groups in Rwanda and to some extent in Kenya. Furthermore, they found that in Tanzania there were few connections with external information sources potentially limiting new innovations entering communities. These results are not unique to Africa. For example, Pachoud et al. (2019) conducted a social network analysis of advice-seeking and an analysis of territorial proximity in Brazil and concluded that extension agents are at the center of the advice network; however, there is a lack of trust and reciprocity among producers leading to low levels of interaction and collective action.

Literature on agricultural producer groups largely accepts that farmers' collective action is greatly engraved in social and cultural context driven by social norms (see e.g. Bijman et al, 2012; Falkowski et al., 2017). In particular, Falkowski et al. (2017) investigated factors that promote positive solutions to coordination problems in rural areas by closely looking at social interactions between individuals who decide to engage in collective action of participating in agricultural producer groups. Their analysis shows that farmers who associate more weight on trust and cooperation organise producer groups around kinship and acquaintanceship relations. Their contribution added to our understanding of how social relations in rural areas are constructed and performed.

Belonging to a social group results in members sharing information about agricultural visits by agricultural extension officers and becomes a conduit through which knowledge is shared resulting in agricultural innovation. Therefore, food security will come from the integration of knowledge from various actors and interdependence, learning and social interaction. This means that participation in social groups (both formal and informal networks) is expected to motivate the exchange of information, establish synergy among members and stimulate access to resources (see ibid.); and that may ensure food security particularly if this leads to productive cooperation. For example, food security is expected to be facilitated by increased interactions between farm households and other actors in agricultural research, development and training.

Interaction within social groups and between members and the extension service is an important part of an agricultural system. Hansen (2015) explored how interaction between two important parties in knowledge system, namely the farmers and the extension service can contribute to better farming performance. In particular, the analysis was on how membership in discussion clubs influences farmers' problem solving behaviour and farm performance; as well as how interaction with consultants through regular farm visits affect farmers' problem solving behaviour. The major conclusions are that through membership, farmers learn to improve their problem solving and that frequent interaction with consultants through regular farm visits helps farmers to become more proactive due to enough and relevant information. Both for farmers and for consultants, extension services add to better problem solving, more proactive behaviour and improved performance.

It has been noted that farmers have managed not only to increase their knowledge but also to actively use it through individual and group learning. Discussion group membership has been found to have a positive impact on farmers’ profits and that farmers’ participation in networks contributed to cheaper animal husbandry practices (Hansen, 2013; cited in Hansen, 2015). This means that social capital contributes to learning through interaction with others which is achieved through shared understanding between members, agricultural extension officers and personal relationships between them. Interacting with others can contribute to viable solutions with the ultimate result of ensuring food security. Social capital, particularly in the definition adopted in this study of belonging to a social group plays an important role.

In the case of agricultural extension and veterinary services, as noted elsewhere in the literature (ibid.), a decline in public extension services results in alternative extension approaches including more participatory approaches such as volunteer-farmer training. Agricultural training of this nature increases household food security. Kumar et al. (2020) found that adoption of improved technologies and practices is significantly increased by, among others, membership in progressive farmers groups and cooperative societies, and participation in agricultural training and farm visits. They also concluded that improved practices increase when farmers obtain information from informal sources, cooperatives/farmers organizations, and public and private extension programs. Therefore, the following hypothesis linking social capital to agricultural extension and veterinary services are proposed:

Hypothesis 3.3.1:

Social capital increases the likelihood of a household receiving agricultural training.

Agricultural technologies can increase crop production thereby improving household food security. Innovations such as enhanced agricultural practices, crop varieties, inputs and related products such as crop insurance have potential to improve household food security (Buisson and Balasubramanya, 2019; Mutenje et al., 2016). These agricultural innovations are facilitated by a wide array of interactions between men and women, households and communities; and are moulded by formal and informal institutions, practices, behaviours and social relations and ride on diffusion of information in local systems (BenYishay and Mobarak, 2019; Fafchamps and Quinn, 2018). Farmers learn about agricultural technology from multiple people before adopt it themselves (Beaman et al., 2018; Morello et al., 2018; Dalemans et al., 2018); and they consult a broad range of formal and informal professional information sources (Fales et al., 2019; Fales et al., 2016; Koutsouris et al. 2017; Lowe et al., 2019). This observation is supported by Fieldsend et al. (2019) in their analysis on sustainable approaches to fostering agricultural knowledge where they observed that most farmers sought advice from several sources; acquire and share the knowledge. Households that receive agricultural advice have greater productivity and greater food security compared to those that do not receive any advice at all (see e.g. Ragasa and Mazunda, 2018). Households with social capital are likely to share the importance of seeking and receiving this kind of advice. Therefore the following hypothesis linking social capital to crop advice is proposed:

Hypothesis 3.3.2:

Social capital increases the likelihood of a household seeking crop advice.

Agricultural extension services include, among others, provision of timely information and the dissemination of innovations to households, farmers, and other rural residents who depend on agriculture. Site-specific extension advice that is better suited to the needs of individual farm households can potentially increase productivity (Oyinbo et al., 2019). It is therefore within the mandate of the extension agents to disseminate best practices and innovations emanating from research on ways of enhancing adaptive potential and resilience of vulnerable people (Niu and Ragasa, 2018; Olorunfemi et al., 2019). This is usually achieved through regular agricultural extension services visits to communities. Some of the approaches that have been used include village-based intermediaries, farmer-to-farmer extension, farmer field days and farmer field schools (see e.g. Kansiime et al., 2019; Baird et al., 2016). Dates of visits become very important and individuals, households and communities tend to share and remind each other on pending and upcoming visits by extension officers. The following hypothesis linking social capital to visits by agricultural extension officers is advanced:

Hypothesis 3.3.3:

Social capital increases the chances of a household receiving a visit from an agricultural extension officer.

Bard et al, (2019) adopted a qualitative approach to conceptualise how and under what circumstances veterinary advice has the potential to support and inspire farmer engagement with behavioural change. They concluded that, while accuracy of veterinary advisory content is valued, it is the relational context of trust; shared veterinarian-farmer understanding; and meaningful interpretation of advice at farmer level that is likely to effect change. The knowledge acquired inevitably filters to other members of the community. On the part of veterinary advisors and for them to obtain knowledge needed to solve complex veterinary queries, advisors use distributed networks and rely on informal 'communities of practice' comprised of bonding social capital and also draw upon bridging social capital from multiple advisors from different advisory professions (see e.g. Klerkx and Proctor, 2013). Given this, the following hypothesis linking social capital to seeking veterinary services is proposed:

Hypothesis 3.3.4:

Social capital increases the likelihood of a household to seek veterinary services

In general, agricultural productivity in developing countries, particularly in Southern Africa, remains low due to limited adoption of innovation. There is some evidence of the role of social networks in technology diffusion (Beaman et al., 2018). However, little rigorous work has been done on how to mobilize local social networks for agricultural innovation (Fafchamps et al., 2020). In agricultural innovation, technology is regarded as an input. Agricultural technologies typically consist of a package of technical objects, guidelines and instructions for improved farming practices; and these may require technical support (Akullo et al., 2018). Technical support increases productivity. Elahi et al. (2018) found that access to advisory services of this nature improves wheat productivity. This means that agricultural innovation through the use of new technologies and practices needs access to resources such as knowledge, training and emotional support. This requires support from different actors such as peers, social capital, advisors, and researchers (see e.g. Cofre-Bravo et al., 2019).

Farming households use all types of social capital to implement and exploit new technologies (see e.g. Hilkens et al., 2018; Hunecke et al., 2017; ibid; Turner et al., 2017). Abdul-Rahaman and Abdulai (2018) found that participation in farmer groups is associated with increased yield and technical efficiency. Relatedly, Kamar et al. (2020) found that in Nepal the probability of the adoption of improved practices is affected by farmers' sources of information concluding that adoption is increased when farmers obtain information from informal sources, cooperatives/farmers organizations, and public and private extension programs. This means that farming innovation is influenced by social networks in which farming households are naturally members to; giving them access to new knowledge (see e.g. Ainembabazi et al., 2017; Jitmun et al., 2020; King et al., 2019). For example, bonding social capital promotes cooperation and connection between farming households thereby facilitating sharing of knowledge, labour and implements (see e.g. Hoang et al., 2016, cited in Cofre-Bravo etal., 2019).

On the other hand, farming households with bridging and linking social capital are likely to have greater ability to amass and assimilate knowledge about new technologies from external sources as well as receiving timely information. Agricultural extension networks, for instance, use model farmers to demonstrate new cultivation techniques and technologies to local communities. This inevitably leads to social learning (see e.g. Macours, 2019; Shikuku, 2019; Takahashi et al., 2020). For example, Marcus and Bhasme (2018) showed that the production and transfer of knowledge occur both horizontally to community members and vertically through linkages with extension agents, research institutions and private sector interests. This implies that households with members belonging to social groups may establish strong inclusion or exclusion mechanisms within their networks so that members are accorded access to information, whereas those without such networks are left out from the knowledge transfer process. This leads to the development of the following hypothesis linking social capital to technical support:

Hypothesis 3.3.5:

Social capital increases the chances of a household receiving technical support during an agricultural season.

Addressing seasonal food insecurity does not only require increased food production, but also taking into account post-harvest losses (Brander et al. 2020). Post-harvest losses during storage have been noted to be substantial in Sub-Saharan Africa due mostly to insect infestation and mould damage (see e.g. Chegere, 2018; Danso et al., 2017; Mutungi et al., 2019; Tesfaye and Tirivayi, 2018). In Zimbabwe, for example, maize postharvest losses range between 15.5 and 17.5 percent (Govere et al., 2019). Brander et al. (2020) discovered that improved on-farm storage reduces seasonal food insecurity of smallholder farmer households. According to them, addressing seasonal food insecurity demands taking into account post-harvest losses during storage. In Kenya, Aggarwal et al. (2018) (cited in Brander et al. (2020)) find that giving community saving clubs hermetic storage bags increases the quantity stored. Hermetic storage bags are effective against insects by stopping accelerated multiplication of insects (see e.g. Abass et al., 2018; Mutambuki et al., 2019; Singano et al., 2019). Relatedly, Purdue Improved Crop Storage bags retain provitamin and caotenoids in biofortified maize genotypes (Nkhata et al., 2019).

In Uganda, Omotilewa et al. (2018) discovered that households that were given an improved maize storage technology stored maize for a longer period and reported a substantial drop in storage losses than the untreated cohorts. In another Randomised Control Trial in Tanzania, Brander et al. (2020) discovered that improved on-farm storage reduces seasonal food insecurity. These post-harvest storage technologies are likely to be shared among families, relatives, neighbours and communities. This is because people prefer to spread knowledge to their acquaintances (Cetto et al., 2018; Walker, 2011; Zheng et al., 2019); and social networks are an important mechanism for diffusing information (Beaman and Dillon, 2018). This leads to the following hypothesis linking social capital to post-harvest treatment of produce against losses:

Hypothesis 3.3.6:

Social capital increases the likelihood of a household to treat its harvest against postharvest losses.

3.3 Data

This research is based on a nationally representative dataset collected annually by the Zimbabwe Vulnerability Assessment Committee (ZIMVAC), which is a consortium of the Government of Zimbabwe, Development Partners, United Nations, NGOs, and Technical Agencies. It is led and regulated by the Government of Zimbabwe and chaired by the Food and Nutrition Council (FNC), a department in the Office of the President. In turn, the FNC is mandated to promote a multi-sectoral response to food insecurity and nutrition.

For the purpose of this study, 2015 ZIMVAC cross-sectional data was selected specifically because it is the only survey that asked whether households had members belonging to a social group. Other later surveys used trust as a measure of social capital, which was not of interest in this research. The 2015 ZIMVAC survey asks household heads whether there is anyone in their household who is a member of a social group. Social groups mentioned in the survey are: community associations, Informal Savings and Loans Associations (ISAL), SACCOs (registered and formal credit and lending), agricultural extension groups, credit unions for inputs/cash, and burial societies. It goes on to ask household heads how many months they have been members to a particular social group, and the benefits of being a member of a particular group to the household. The respondents were given an option to indicate whether the benefits were: information sharing; access to credit/loans; learning from each other; pooling resources for production; group marketing; or not.

The dataset has 10,708 households and descriptively, 22 percent of households have members belonging to a social group. Table 3.1 below shows descriptive statistics of household characteristics. The average age of household heads with members belonging to a social group is higher at 52 years than those without. They also have more education and bigger households than those without membership. On average, relatively more household heads with members belonging to a social group are female and married than those without.

Table 3.1: Descriptive Statistics: Household Characteristics

	Comparison group (1)	Treatment group (2)	Mean diff. (3)
Household head's age	48.65	51.36	-2.71***
	(17.71)	(15.85)	
Household size	4.90	5.42	-0.52***
	(2.09)	(2.06)	
Household head is female	0.35	0.37	-0.02**
	(0.48)	(0.48)	
Household head is married	0.70	0.72	-0.02**
	(0.46)	(0.45)	
Household head is divorced	0.05	0.03	0.01***
	(0.21)	(0.18)	
Head's education: O level	0.22	0.26	-0.03***
	(0.42)	(0.44)	
Head has no education	0.23	0.18	0.04***
	(0.42)	(0.39)	
Observations	8,307	2,338	

Notes: Standard Deviations in parenthesis. Mean Differences in Column (3) were calculated using t-tests and before Propensity Score Matching. Treatment Group is comprised of households with members belonging to a social group. Comparison Group is comprised of households without social capital. *** p<0.01, ** p<0.05, * p<0.1

The outcome of interest is household food security and this study employs mainly single-item indicators to measure it. These single-item indicators have recently received favour and are widely accepted as valid indicators and proxies of food security (see e.g. Jackson et al., 2019; Lee et al, 2016; Narain et al., 2018). Table 3.2 shows descriptive statistics for different food security pillars. Food Security Pillar 1 describes household food security from cereals stocks and food crops; Pillar 2 = household food security from cereals stocks, food crops and cash crops; Pillar 3 = household food security from cereals stocks, food crops, cash crops, and livestock; Pillar 4 = household food security from cereals stocks, food crops, cash crops, livestock, and remittances; and Food Security Pillar 5 = household food security from cereals stocks, food crops, cash crops, livestock, remittances, and income. On average, households with members belonging to social groups are more food secure than those without.

Table 3.2: Descriptive Statistics: Dependent Variables – Food Security

	Comparison group (1)	Treatment group (2)	Mean diff. (3)
Food security Pillar 1	0.18	0.21	-0.02**
	(0.39)	(0.40)	
Food security Pillar 2	0.21	0.23	-0.01
	(0.41)	(0.42)	
Food security Pillar 3	0.27	0.34	-0.07***
	(0.44)	(0.47)	
Food security Pillar 4	0.31	0.37	-0.06***
	(0.46)	(0.48)	
Food security Pillar 5	0.83	0.90	-0.07***
	(0.38)	(0.30)	
Observations	8,357	2,351	

Notes: Standard Deviations are in parenthesis. The Mean Differences in Column (3) were calculated using t-tests and before Propensity Score Matching. Treatment Group is comprised of households with members belonging to a social group and the Comparison Group is comprised of households without. Food Security Pillar 1 = household food security from cereals stocks and food crops; Pillar 2 = household food security from cereals stocks, food crops and cash crops; Pillar 3 = household food security from cereals stocks, food crops, cash crops, and livestock; Pillar 4 = household food security from cereals stocks, food crops, cash crops, livestock, and remittances; and Food Security Pillar 5 = household food security from cereals stocks, food crops, cash crops, livestock, remittances, and income. Each food security pillar is binary indicating whether a household is food secure in the pillar or not. *** p<0.01, ** p<0.05, * p<0.1

Household food security in this study is also measured by binary responses to whether there was a day in the past 30 days when there was no food to eat; there was any household member who went to sleep at night hungry in the past 30 days; and whether any household member went a whole day and night hungry in the past 30 days; or not. These were conveniently called Household Hunger Scale 1, Household Hunger Scale 2 and Household Hunger Scale 3, respectively as shown in Table 3.3. On average, 23 percent of households without any member belonging to a social group report having a day when there was no food compared to only 15 percent for households with social capital. Sleeping without eating anything is an implicit measure of the severity of food insecurity. Of the households without any of their members belonging to a social group, 22 percent reported ever going to sleep at night without eating anything compared to 18 percent of those with social capital. Only 6 percent of households with members belonging to a social group ever went a whole day and night hungry compared with 11 percent of households without social capital. On average, relatively a higher proportion of households without social capital experience hunger than those with social capital.

Table 3.3: Descriptive Statistics: Dependent Variables – Household Hunger

	Comparison Group (1)	Treatment Group (2)	Mean diff. (3)
Household hunger scale 1	0.23	0.15	0.08***
	(0.42)	(0.36)	
Household hunger scale 2	0.22	0.18	0.04***
	(0.41)	(0.39)	
Household hunger scale 3	0.11	0.06	0.04***
	(0.31)	(0.24)	
Observations	8,357	2,351	

Notes: Standard Deviations in parenthesis. Treatment group is comprised of households with members belonging to a social group and Comparison Group is comprised of households without. The Mean Differences in Column (3) were calculated using t-tests and before Propensity Score Matching. Household Hunger Scale 1 = whether there was a day in the past 30 days when there was no food to eat; Household Hunger Scale 2 = whether there was any household member who went to sleep at night hungry in the past 30 days; and Household Hunger Scale 3 = whether any household member went a whole day and night hungry in the past 30 days. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

When faced with food insecurity shocks, households tend to adopt coping strategies such as skipping meals, limiting portion size at meal, and reducing the number of meals. Table 3.4 below shows descriptive statistics on behavioural hunger-coping strategies by treatment and control groups. Treatment group is comprised of households with members belonging to a social group and control group is comprised of households without any member belonging to a social group. Only 9 percent of households in the treatment group resort to skipping meals compared to 15 percent of households in the control group. The proportion of households resorting to limiting meal portion sizes and reducing the number of meals is high in both the treatment and control groups although with significant differences between the groups. Sixty percent of households in the control group report limiting portion size of meals compared to 56 percent of households in the treatment group. On the other hand, 61 percent and 55 percent reduce the number of meals in the control and treatment groups, respectively. Forty-six and 42 percent of households without social capital and those with social capital resort to borrowing food, respectively.

Table 3.4: Descriptive Statistics: Dependent Variables – Coping Strategies

	Comparison group (1)	Treatment group (2)	Mean diff. (3)
Skipping meals	0.15	0.09	0.06***
	(0.36)	(0.29)	
Limiting portion size	0.61	0.56	0.05***
	(0.49)	(0.50)	
Reducing number of meals	0.60	0.55	0.05***
	(0.49)	(0.50)	
Borrowing food	0.46	0.42	0.04***
	(0.50)	(0.49)	
Observations	8,357	2,351	

NOTES: Standard Deviations in parenthesis. Treatment group is comprised of households with members belonging to a social group and Comparison Group is comprised of households without. The Mean Differences in Column (3) were calculated using t-tests and before Propensity Score Matching. *** p<0.01, ** p<0.05, * p<0.1

Table 3.5 shows descriptive statistics for dependent variables of agricultural extension and veterinary services by treatment and control groups. The survey asked household heads whether a household received any agricultural training in the 2014/2015 agricultural season, they received any visit by an Agricultural Extension Officer, any member of the household sought any cropping advice during the cropping season, any household member sought veterinary services, a household received any technical support during the agricultural season, and whether a household treat its harvest against post-harvest losses; or not. As can be seen from Table 3.5, the mean differences between households with members belonging to a social group and those without are huge. Fifty-seven percent of households with members belonging to a social group received agricultural training compared to only 33 percent of households without social capital. On the other hand, 47 percent of households with social capital had a visit from an Agricultural Extension Officer compared to only 29 percent for households without social capital.

Table 3.5: Descriptive Statistics: Dependent Variables - Agricultural Extension Services

	Comparison Group (1)	Treatment Group (2)	Mean diff. (3)
Agricultural training	0.33	0.57	-0.24***
	(0.47)	(0.49)	
Agritex visit	0.29	0.47	-0.19***
	(0.45)	(0.50)	
Seek crop advice	0.23	0.40	-0.17***
	(0.42)	(0.49)	
Seek veterinary services	0.18	0.32	-0.14***
	(0.38)	(0.47)	
Technical support	0.20	0.36	-0.16***
	(0.40)	(0.48)	
Treat harvest	0.55	0.72	-0.16***
	(0.50)	(0.45)	
Observations	8,357	2,351	

NOTES: Standard Deviations in parenthesis. Treatment group is comprised of households with members belonging to a social group and Comparison Group is comprised of households without. The Mean Differences in Column (3) were calculated using t-tests and before Propensity Score Matching. Agric Training = whether a household received any agricultural training in the 2014/2015 agricultural season. Agritex Visit = whether a household received any visit by an Agricultural Extension Officer. Seek Crop Advice = whether any member of the household sought any cropping advice during the cropping season. Seek Vet Services = whether any household member sought veterinary services. Tech Support = whether a household received any technical support during the agricultural season. Treat Harvest = whether a household treat its harvest against rodents and weevils. *** p<0.01, ** p<0.05, * p<0.1

Relatedly, only 23 percent of households in the comparison group sought crop advice compared to 40 percent of households in the treatment group. Seeking crop advice is likely to be associated with good yields and may ensure food security. Eighteen percent of households in the comparison group sought veterinary services compared to 32 percent of households in the treatment group and only 20 percent of them sought technical support compared with 36 percent of households in the treatment group. Food security is also ensured by preserving harvests from rodents and weevils and other causes of post-harvest losses. Seventy-two percent of households in the treatment group treat their harvest against post-harvest losses compared to only 55 percent from the comparison group.

Almost all the differences in means from Table 3.1 to Table 3.5 are significantly different from zero. This means that on average, having social capital improves welfare and is associated with food security. This also brings in another interesting scenario from a methodological point of view. In finding the effect of an intervention, it is important to make sure that the treatment and control groups are comparable. This issue is sufficiently dealt with in the next section on methodology.

3.4 Methodology

3.4.1 Empirical Strategy

Social capital is potentially endogenous and as such experimental and quasi-experimental empirical strategies are the most appropriate to establish effects. The definition of social capital adopted in this study is a binary response on whether a household has a member who belongs to a social group. This measure is likely to suffer from selection bias if there are systematic and unobserved characteristics that make certain members and households self-select themselves into social groups more than others who do not possess such characteristics. This study is not a Randomised Controlled Trial (RCT) and as such the effect of social capital on food security outcome variables can be subject to treatment selection bias in which households with members belonging to a social group may differ systematically from households with no member belonging to a social group.

In light of the above arguments, Propensity Score Matching is therefore adopted in this research. Propensity Score Matching is increasingly used to estimate treatment effects using observational data (Austin, 2009; Ali et al., 2015; Fullerton, 2016; Garrido et al., 2014; Lee and Little, 2017; Linden and Samuels, 2013). A propensity score is a single score that in this case will represent the probability of a household having a member who belongs to a social group, conditional on a set of observed covariates. Conditional on the true propensity score, belonging to a social group is independent of measured baseline covariates. In other words, treated and untreated households with the same propensity score will have similar distributions of observed baseline covariates (see Rosenbaum and Rubin, 1983; 1984). This means that propensity scores are important when estimating a treatment's effect on an outcome using observational data and when selection bias due to non-random treatment assignment is likely. Propensity scores therefore provide a way to balance measured covariates across households with members belonging to a social group and households without and better approximates the counterfactual for treated households. A probit model used to calculate the propensity score can be summarized as follows:

$$P(S_i = 1|X_i) = F(X_i\beta) \quad (1)$$

The empirical strategy is motivated as follows:

$$ATT = E[Y_1 - Y_0 \mid S = 1\,] \quad (2)$$

where Y_1 is the potential outcome in the case of a household having a member belonging to a social group. Y_0 is the potential outcome if a household does not have any of its members belonging to a social group. S is binary, with $S = 1$ if the household has a member belonging to a social group and $S = 0$ otherwise. X_i is a vector of covariates that influence social capital and β is $1\ x\ k$ vector of coefficients. $F(X_i\beta)$ is a cumulative probability function of the standard normal distribution. ATT is the Average Treatment Effect on the Treated and ATT is only identified when the outcomes of households from the treatment and comparison groups do not differ in the absence of treatment. That is if:

$$E[Y_0|\ S = 1\,] - (E[Y_0|\ S = 0]) = 0 \quad (3)$$

To achieve that in an observational study such as this one, requires relying on some identifying assumptions. The first assumption requires that assignment to treatment be independent of the outcomes, conditional on the covariates, X, -:

$$[Y_0; Y_1] \perp\!\!\!\perp S \mid X \quad (4)$$

The second assumption is the overlap or common support condition. The probability of assignment should be bounded away from zero and one:

$$0 < \Pr(S = 1 \mid X) < 1 \tag{5}$$

This means that with the common support assumption, the assignment mechanism can be interpreted as if, within subpopulations of units with the same value for the covariate, totally randomised experiment was carried out and data can be analysed from subsamples with the same value of the covariates under such interpretation (Grilli and Rampichini, 2011). When these two assumptions are satisfied then the treatment can be referred to as being strongly ignorable (see Rosenbaum and Rubin, 1983). Unfortunately, the strongly ignorable treatment assignment assumption cannot be empirically tested.

Propensity Score Matching method attempts to imitate the randomised assignment to treatment and comparison groups by selecting from the comparison group those households that have similar propensities to households in the treatment group. The impact of social capital on food security is therefore estimated by comparing the average outcomes of a household with a member belonging to a social group and the average outcome among a statistically matched subgroup from households without any of its members belonging to a social group. This match is achieved based on observed characteristics available in the ZIMVAC data.

3.4.2 Choice of variables in the calculation of the propensity score

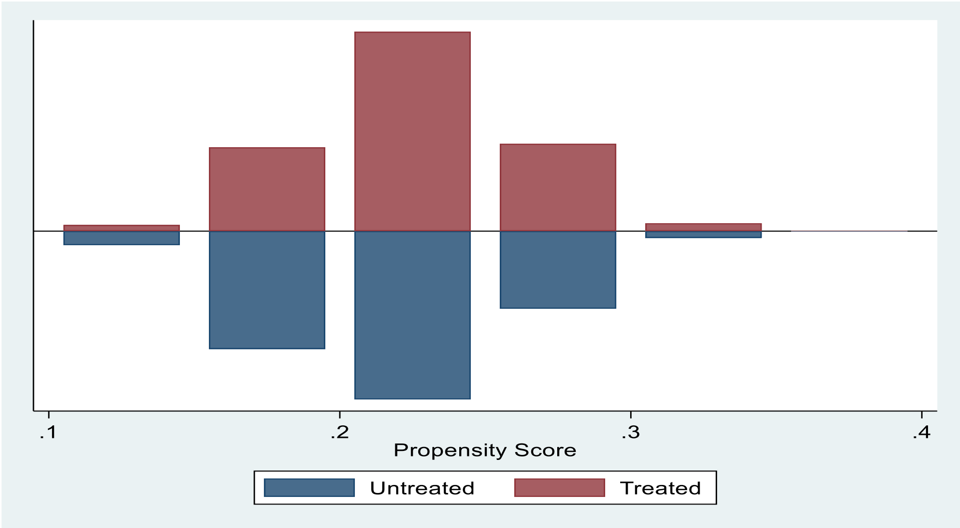
The major consideration in selecting variables to be used in the calculation of a propensity score is the trade off between bias and efficiency. In choosing variables, attention was paid to variables that are potentially related to food security but not social capital. Variables associated with social capital but not food security were left out because they do not address confounding and are irrelevant for the purposes of the propensity score. Covariates affected by social capital were left out because they potentially mask part of the treatment effect being estimated (see e.g. Garrido et al., 2014). Related, variables that perfectly predict social capital were also left out in the calculation of the propensity score because they do not achieve sufficient overlap in some degree between households with members belonging to a social group and those without.

The selection of variables for the calculation of the propensity score was limited to household head's age, gender of the household head, marital status of the household head, household head's education and village, so as to keep the variables that are potentially related to both social capital and food security and to disregard those that are weakly associated with food security. Using all covariates was avoided in order to circumvent bias arising from selecting a wide bandwidth in response to the weakness of the common support. Including insignificant covariates in the propensity score specification would lead to inefficiency since this would increase the variance of the propensity score estimates.

3.4.3 Balance on the propensity score

It is here that the overlap assumption is addressed. A large area of common support gives confidence and assurance that the observed treatment effect satisfies external validity. Therefore, it is important to ensure that there is overlap in the range of propensity scores across households with members who belong to a social group and those that do not. This was achieved by subjectively examining graphs of propensity scores across treatment and comparison groups. For example, Figure 3.1 shows the overlap of the distribution of the propensity scores across households with a member belonging to a social group (treatment group) and households without (control group). As can be seen from the graph on the check of the range of common support, balance was achieved across treatment and comparison groups. It was also ensured that the distribution of the propensity score is similar between treatment and comparison groups by splitting the entire sample into quintiles (see e.g. Lee and Little, 2017).

Figure 3.1: A Check on the Range of Common Support



3.4.4 Balance on the Covariates

In order to ensure that the propensity score's distribution is not different across groups and that the propensity score is appropriately specified, a check for balance of individual covariates across households with members belonging to a social group and those without within blocks of the propensity score was carried out. This was to ensure that treatment and comparison groups are comparable on baseline characteristics so as to guarantee valid results. To achieve this, standardised differences were calculated. Figure 2 below displays visual inspection of standardised differences for unmatched and matched samples. Before matching, standardized percentage bias across covariates ranged from -8% and 16% but after matching it was significantly reduced to between 0 and 4.5%.

Figure 3.2: Visual Inspection of Standardized Differences

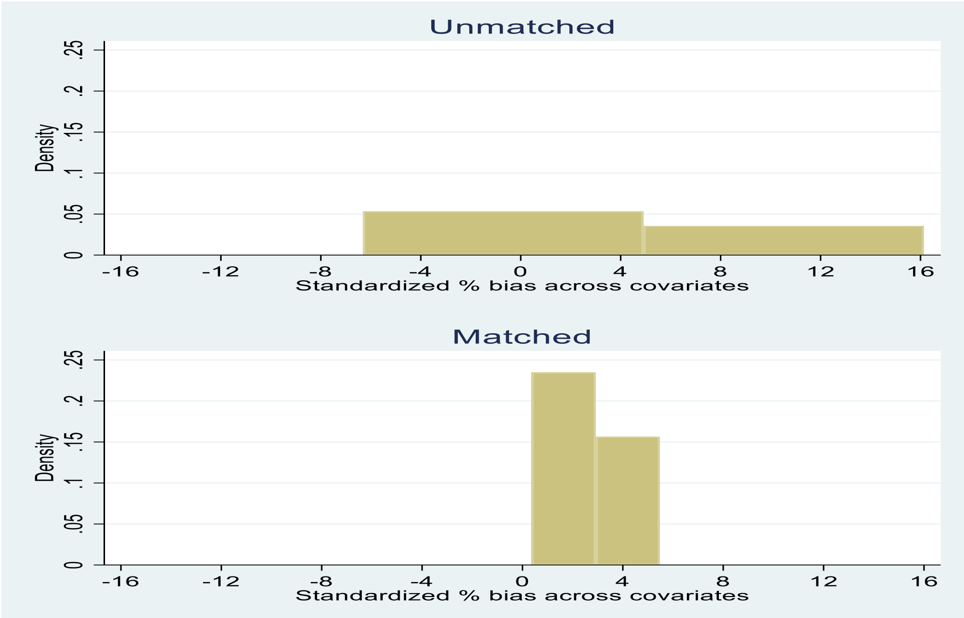


Table 3.6 shows standardised differences across covariates after matching. All standardized differences after matching across covariates are all less than 0.03. This confirms that the covariates are balanced and the propensity score's distribution is similar across groups. Although there is no rule regarding how much imbalance is acceptable, standardised differences of less than 0.03 are, by all standards very small and acceptable.

Table 3.6: Standardized Differences across Covariates after Matching

	Mean in treated (1)	Mean in untreated (2)	Standardized diff. (3)
Head's Age	49.72	49.29	0.026
Head is Female	0.36	0.36	0.016
Head is divorced	0.04	0.04	0.002
Head has 'O'Level	0.23	0.23	-0.006

NOTES: Treatment Group is comprised of households with members belonging to a social group. Comparison Group is comprised of households without any member belonging to a social group.

The smaller the differences are, the better. Literature points to anything from 0.10 to 0.25 as being indicative of imbalance (Austin, 2009; Garrido et al., 2014; Linden and

Samuels, 2013; Normand et al, 2001; Rubin, 1973). Using standardised differences other than t-tests and any other such diagnostic tool is appropriate in that standardised differences are dimensionless and are not influenced by sample size. Therefore they can be used to compare balance in measured covariates between households with members belonging to a social group and those without in the matched sample with that in the unmatched sample. Figure 3.3 below also confirms that balance across continuous covariates was also achieved. The figure shows a density plot of household head's age for treatment and control groups after matching and the visual inspection shows that they were indeed balanced and the distribution is similar in both the treatment and control groups.

Figure 3.3: Density Plot for Household Head's Age in Treated and Comparison Groups after Matching

3.4.5 Matching and weighting strategies

The choice of matching and weighting strategy is, to a large extend, influenced by the trade-off between bias and efficiency. Nearest Neighbour matching and the Inverse-Probability Treatment Weights (IPTW) were chosen for this study. Nearest Neighbour was chosen because it often produces well balanced samples. Each household with members belonging to a social group was matched to one comparable household without. This one-to-one matching algorithm was preferred because it leads to least biased estimates and efficiency was not much of a concern because of large number of observations in the dataset. The Nearest Neighbour matching estimator is motivated as:

$$ATT^{NN} = \frac{1}{N^T} \sum_{i:W_i=1} \left[Y_i^{obs} - \sum_{j \epsilon C(i)_M} W_{ij} \; Y_j^{obs} \right] \tag{6}$$

$$= \frac{1}{N^T} \sum_{i:W_i=1} Y_i^{obs} - \frac{1}{N^T} \sum_{j \epsilon C(i)_M} W_j Y_j^{obs} \tag{7}$$

where N^T is the number of households with members belonging to a social group; N_i^C is the number of households without; W_{ij} is equal to $\frac{1}{N_i^C}$ if j is a control units of i and zero otherwise; and $W_j = \sum_i w_{ij}$. As for the Inverse-Probability Treatment Weights, each household with members belonging to a social group receives a weight equal to the inverse of the propensity score and each comparable household without social capital is given a weight equal to the inverse of one minus the propensity score.

3.5. Results

In assessing the impact of social capital on food security, a number of food security related outcome variables were used. These included food security pillars, household hunger scales, coping strategies and agricultural extension and veterinary services related outcome variables. Table 3.7 below shows estimation results of the impact of social capital on 5 different food security pillars. Food Security Pillars from 1 to 5 are binary, based on whether a household is food secure to the described categories or not. Food Security Pillar 1 is based on household food security from cereals stocks and food crops. Pillar 2 is based on household food security from cereals stocks, food crops and cash crops; and Pillar 3 on food security from cereals stocks, food crops, cash crops, and livestock. Relatedly, Pillar 4 is concerned with household food security from cereals stocks, food crops, cash crops, livestock, and remittances. Finally, Food Security Pillar 5 is likewise based on household food security from cereals stocks, food crops, cash crops, livestock, remittances, and income.

Panel A of Table 3.7 shows Nearest Neighbour Matching results. These results measure average treatment effect on the treated. Households with social capital are more food secure than those without. The impact is significant at 1 percent for Food Security Pillars 3 to 6. Households with members belonging to a social group have a 6 percentage point higher chance of being food secure in cereal stocks, food crops, cash crops, and livestock and an 8 percentage point higher chance of being food secure for Food Security Pillar 6 than those without members who belong to a social group.

These results are confirmed in Panel B and Panel C in the table. Panel B shows Kernel Weighted Estimations of the impact of social capital on food security. These results are consistent with results in Panel A of the table except that the results are now also picking significance at 1 percent for Food Security Pillar 1. The estimated effect and level of significance are similar for Nearest Neighbour matching results in Panel A and those in Panel B for Food Security Pillars 3 to 6. These findings are also supported by results in Panel C of the table, which shows Inverse-Probability Treatment Weight results of the impact of social capital on food security. These results support hypothesis 3.1.1 confirming that social capital has an impact on household food security. This result supports Jackson et al. (2019) who found that social capital is positively associated with food security.

In general, households that are food insecure are likely to experience incidences of hunger. This may involve experiences of lean days in which households may spend some days without food or even retiring to bed without eating anything. Table 3.8 presents results on the impact of social capital on household hunger. The table has three panels showing Nearest Neighbour Matching, Kernel Weighted and Inverse-Probability of Treatment Weight estimation results, respectively. The results are also presented based on specific household hunger questions. Household Hunger Scale 1 is based on whether there was a day in the past 30 days when there was no food to eat. Household Hunger Scale 2, in turn, is based on whether there was any household

Table 3.7: Average Treatment Effect on the Treated (ATT) of Social Capital on Food Security

PANEL A: NEAREST NEIGHBOR MATCHING

	Food Security Pillar 1	Food Security Pillar 2	Food Security Pillar 3	Food Security Pillar 4	Food Security Pillar 5
Social Capital	0.017	0.004	0.058***	0.055***	0.082***
	(0.013)	(0.013)	(0.015)	(0.015)	(0.012)
Observations	10,645	10,645	10,645	10,645	10,645

PANEL B: KERNEL WEIGHT RESULTS OF SOCIAL CAPITAL ON FOOD SECURITY

	Food Security Pillar 1	Food Security Pillar 2	Food Security Pillar 3	Food Security Pillar 4	Food Security Pillar 5
Social Capital	0.019***	0.008	0.060***	0.053***	0.072***
	(0.003)	(0.011)	(0.001)	(0.011)	(0.012)
Observations	10,645	10,645	10,645	10,645	10,645

PANEL 3: IPTW RESULTS OF SOCIAL CAPITAL ON FOOD SECURITY

	Food Security Pillar 1	Food Security Pillar 2	Food Security Pillar 3	Food Security Pillar 4	Food Security Pillar 5
Social Capital	0.020**	0.011	0.062***	0.054***	0.073***
	(0.009)	(0.010)	(0.011)	(0.011)	(0.008)
Observations	10,645	10,645	10,645	10,645	10,645

NOTES: Results based on 2015 ZIMVAC data. The probability of treatment is based on a probit model. Social Capital is binary (=1 if a household has a member who belongs in a social group). Food Security Pillars from 1 to 5 above are binary. Food Security Pillar 1 = household food security from cereals stocks and food crops; Pillar 2 = household food security from cereals stocks, food crops and cash crops; Pillar 3 = household food security from cereals stocks, food crops, cash crops, and livestock; Pillar 4 = household food security from cereals stocks, food crops, cash crops, livestock, and remittances; and Food Security Pillar 5 = household food security from cereals stocks, food crops, cash crops, livestock, remittances, and income. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

member who went to sleep at night hungry in the past 30 days; and Household Hunger Scale 3 on whether any household member went a whole day and night hungry in the past 30 days.

The results show that households with social capital are less likely to experience a day when there was no food to eat, less likely to have household members who went to sleep at night hungry, and less likely to go a whole day and night hungry compared to those without. The results are consistent and significant at 1 percent in all the three matching algorithms used in this study and for all the household hunger scales. For example, households with members belonging to a social group have a 7.8 percentage point lower chance of experiencing a day when there was no food to eat; a 4.7 percentage point lower chance of having a member who went to sleep at night hungry; and a 4.6 percentage point lower chance of having a member going a whole day and night hungry than those without members belonging to a social group. These results confirm hypothesis 3.1.2 and are consistent with the findings of Martin et al (2004) who concluded that social capital is positively associated with decreased risk of hunger.

When faced with food insecurity, households are forced to adopt coping strategies including skipping meals, limiting portion size at meal, reducing the number of meals, borrowing food, eating less expensive food and sometimes eating immature crops. Relatively more food secure households are less likely to adopt these strategies. In order to assess the impact of social capital on these coping strategies, matching estimations were carried out and the results are presented in Table 3.9, Table 3.10 and Table 3.11.

Table 3.9 presents Nearest Neighbour Matching estimation results. The table comprises of results for the impact of social capital on 12 coping strategies. Coping Strategy 1 is based on whether a household skipped an entire day without eating and Coping Strategy 2 on limiting portion size at meal. Coping Strategy 3 = reducing number of meals eaten; Coping Strategy 4 = borrowing food. Household Coping Strategy 5 = relying on less expensive food; Coping Strategy 6 = harvesting immature food crops; Strategy 7 = sending household members to eat with neighbours; and Coping Strategy 8 = sending household members to beg.

Table 3.8: Impact of Social Capital on Household Hunger Scale

PANEL A: NEAREST NEIGHBOR ESTIMATIMATIONS

	Hunger Scale 1	Hunger Scale 2	Hunger Scale 3
Social Capital	-0.078***	-0.047***	-0.046***
	(0.013)	(0.013)	(0.009)
Observations	10,645	10,645	10,645

PANEL B: KERNEL WEIGHT ESTIMATIONS

	Hunger Scale 1	Hunger Scale 2	Hunger Scale 3
Social Capital	-0.073***	-0.031***	-0.043***
	(0.009)	(0.001)	(0.003)
Observations	10,645	10,645	10,645

PANEL C: INVERSE-PROBABILITY OF TREATMENT WEIGHT ESTIMATIONS

	Hunger Scale 1	Hunger Scale 2	Hunger Scale 3
Social Capital	-0.076***	-0.034***	-0.044***
	(0.009)	(0.009)	(0.006)
Observations	10,645	10,645	10,645

NOTES: Results based on 2015 ZIMVAC data. The probability of treatment is based on a probit model. Social Capital is binary (=1 if a household has a member who belongs in a social group). Household Hunger Scale 1 to 3 above are binary. Household Hunger Scale 1 = whether there was a day in the past 30 days when there was no food to eat; Household Hunger 2 = whether there was any household member who went to sleep at night hungry in the past 30 days; and Household Hunger 3 = whether any household member went a whole day and night hungry in the past 30 days. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Household Coping Strategy 9 = purchasing food on credit; Coping Strategy 10 = gathering food and hunting; Coping Strategy 11 = reducing adult consumption; and Coping Strategy 12 = relying on casual labour for food.

The results show that households with members belonging to a social group, when compared to households without, have a: 6.6 percentage point lower chance of skipping an entire day without eating; 5.4 percentage point lower chance of limiting portion size of meals; 4.3 percentage point lower chance of borrowing food; 8.2 percentage point lower chance of relying on less expensive food; 8.5 percentage point lower chance of harvesting immature food crops; 3.4 percentage point lower chance of sending household members to eat with neighbours; 5.4 percentage point lower chance of sending members to beg; 2.5 percentage point lower chance of purchasing food on credit; 3.3 percentage point lower chance of gathering food and hunt; 6.5 percentage point lower chance of reducing adult consumption; and a 6.1 percentage point lower chance of relying on casual labour for food. All the estimates are significant at 1 percent except for the estimate for Coping Strategy 9: purchasing food on credit, which is weakly significant.

To check for robustness, Kernel-Weighted and Inverse-Probability of Treatment Weight results are presented in Table 3.10 and Table 3.11, respectively. Results in Table 3.10 are consistent with results in Table 3.9: Households with social capital are less likely to adopt the outlined coping strategies compared to households without. All the estimates are also significantly different from zero at the 1 percent level except for Coping Strategy 9: purchasing food on credit, which is also weakly significant. These results are also confirmed in the Inverse-Probability of Treatment Weight results in Table 3.11. All the estimates are strongly significant. However, the estimate for Coping Strategy 9 is now significant at 5 percent when compared to results in Table 3.9 and Table 3.10.

These results therefore support hypothesis 3.2 that households with members belonging to a social group are less likely to engage in behavioural hunger-coping strategies that include skipping meals through to relying on casual labour for food. Martin and Lippert (2012) observed that food-insecure mothers skip meals. Relatedly, Ncube et al. (2018) concluded that women skip meals and reduce meal portions and Puddephatt et al. (2020) reported that the food-insecure indicate

Table 3.9: Nearest Neighbour Estimation Results of the Impact of Social Capital on Household Coping Strategy

	Coping Strategy 1	Coping Strategy 2	Coping Strategy 3	Coping Strategy 4
Social Capital	-0.066***	-0.054***	-0.052***	-0.043***
	(0.011)	(0.016)	(0.016)	(0.016)
Observations	10,645	10,645	10,645	10,645

	Coping Strategy 5	Coping Strategy 6	Coping Strategy 7	Coping Strategy 8
Social Capital	-0.082***	-0.085***	-0.034***	-0.054***
	(0.016)	(0.016)	(0.009)	(0.009)
Observations	10,645	10,645	10,645	10,645

	Coping Strategy 9	Coping Strategy 10	Coping Strategy 11	Coping Strategy 12
Social Capital	-0.025*	-0.033***	-0.065***	-0.061***
	(0.015)	(0.012)	(0.016)	(0.015)
Observations	10,645	10,645	10,645	10,645

NOTES: Average Treatment Effects on the Treated Results based on 2015 ZIMVAC data and nearest neighbor matching. The probability of treatment is based on a probit model. Social Capital is binary (=1 if a household has a member who belongs in a social group). Household Coping Strategy from 1 to 12 above are binary. Coping Strategy 1 = skipping entire day without eating; Coping Strategy 2 = limiting portion size at meal; Coping Strategy 3 = reducing number of meals eaten; Coping Strategy 4 = borrowing food. Household Coping Strategy 5 = relying on less expensive food; Coping Strategy 6 = harvesting immature food crops; Strategy 7 = sending household members to eat with neighbors; and Coping Strategy 8 = sending household members to beg. Household Coping Strategy 9 = purchasing food on credit; Coping Strategy 10 = gathering food and hunting; Coping Strategy 11 = reducing adult consumption; and Coping Strategy 12 = relying on casual labor for food. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 3.10: Kernel-Weight Results of Impact of Social Capital on Household Coping Strategy

	Coping Strategy Pillar 1	Coping Strategy Pillar 2	Coping Strategy Pillar 3	Coping Strategy Pillar 4
Social Capital	-0.058***	-0.049***	-0.047***	-0.034***
	(0.001)	(0.016)	(0.010)	(0.001)
Observations	10,645	10,645	10,645	10,645

	Coping Strategy Pillar 5	Coping Strategy Pillar 6	Coping Strategy Pillar 7	Coping Strategy Pillar 8
Social Capital	-0.055***	-0.068***	-0.033***	-0.052***
	(0.004)	(0.004)	(0.008)	(0.003)
Observations	10,645	10,645	10,645	10,645

	Coping Strategy Pillar 9	Coping Strategy Pillar 10	Coping Strategy Pillar 11	Coping Strategy Pillar 12
Social Capital	-0.019**	-0.031***	-0.047***	-0.063***
	(0.009)	(0.003)	(0.000)	(0.016)
Observations	10,645	10,645	10,645	10,645

NOTES: Average Treatment Effects on the Treated Results based on 2015 ZIMVAC data and Kernel Weighted matching. The probability of treatment is based on a probit model. Social Capital is binary (=1 if a household has a member who belongs in a social group). Household Coping Strategy from 1 to 12 above are binary. Coping Strategy 1 = skipping entire day without eating; Coping Strategy 2 = limiting portion size at meal; Coping Strategy 3 = reducing number of meals eaten; Coping Strategy 4 = borrowing food. Household Coping Strategy 5 = relying on less expensive food; Coping Strategy 6 = harvesting immature food crops; Strategy 7 = sending household members to eat with neighbours; and Coping Strategy 8 = sending household members to beg. Household Coping Strategy 9 = purchasing food on credit; Coping Strategy 10 = gathering food and hunting; Coping Strategy 11 = reducing adult consumption; and Coping Strategy 12 = relying on casual labor for food. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 3.11: IPTW Results of the Impact of Social Capital on Household Coping Strategy

	Coping Strategy Pillar 1	Coping Strategy Pillar 2	Coping Strategy Pillar 3	Coping Strategy Pillar 4
Social Capital	-0.060***	-0.048***	-0.051***	-0.035***
	(0.007)	(0.012)	(0.012)	(0.012)
Observations	10,645	10,645	10,645	10,645

	Coping Strategy Pillar 5	Coping Strategy Pillar 6	Coping Strategy Pillar 7	Coping Strategy Pillar 8
Social Capital	-0.056***	-0.065***	-0.035***	-0.052***
	(0.012)	(0.011)	(0.006)	(0.006)
Observations	10,645	10,645	10,645	10,645

	Coping Strategy Pillar 9	Coping Strategy Pillar 10	Coping Strategy Pillar 11	Coping Strategy Pillar 12
Social Capital	-0.019*	-0.033***	-0.042***	-0.060***
	(0.011)	(0.008)	(0.011)	(0.011)
Observations	10,645	10,645	10,645	10,645

NOTES: Average Treatment Effects on the Treated Results based on 2015 ZIMVAC data and Inverse-Probability of Treatment Weight matching. The probability of treatment is based on a probit model. Social Capital is binary (=1 if a household has a member who belongs in a social group). Household Coping Strategy from 1 to 12 above are binary. Coping Strategy 1 = skipping entire day without eating; Coping Strategy 2 = limiting portion size at meal; Coping Strategy 3 = reducing number of meals eaten; Coping Strategy 4 = borrowing food. Household Coping Strategy 5 = relying on less expensive food; Coping Strategy 6 = harvesting immature food crops; Strategy 7 = sending household members to eat with neighbors; and Coping Strategy 8 = sending household members to beg. Household Coping Strategy 9 = purchasing food on credit; Coping Strategy 10 = gathering food and hunting; Coping Strategy 11 = reducing adult consumption; and Coping Strategy 12 = relying on casual labor for food. Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

restrictive eating patterns. However, these behavioural hunger-coping strategies may lead to health challenges such as illnesses, mental health problems and poor quality of life as well as depressive disorder (Daniel, 2020; Kwak and Kim, 2017; Lee et al., 2017). This means that social capital, as confirmed in Tables 3.9 through to Table 3.11, is an implicit social protection program that albeit improves health and welfare.

Agricultural extension and veterinary services provide advisory services that may increase food security. In order to assess the impact of social capital on household food security, agricultural extension and veterinary related outcome variables were used. This included binary variables such as agricultural training, agricultural extension visits, and crop advice. These results are presented in Tables 3.12, 3.13 and 3.14. Results in Column 1 in each table are based on 'Agric Training' measuring whether a household received any agricultural training in the 2014/2015 agricultural season. Column 2 presents results for 'Agritex Visit' based on whether a household received any visit by an Agricultural Extension Officer and Column 3 shows results for 'Seek Crop Advice' based on whether any member of the household sought any cropping advice during the cropping season. Likewise, Column 4 displays results for 'Seek Vet Services' premised on whether any household member sought veterinary services and Column 5 for 'Tech Support' based on whether a household received any technical support during the agricultural season. Finally, Column 6 is based on 'Treat Harvest' measuring whether a household treats its harvest against post-harvest losses, or not.

Table 3.12 presents Nearest Neighbour Matching results and all the estimates are positive and significant at 1 percent. A household with social capital has a 23 percentage point higher chance of participating in agricultural training than one without social capital; an estimate which is significant at the 1 percent level. Relatedly, a household with social capital has an 18 percentage point higher chance of both receiving a visit by an agricultural extension officer and of seeking crop advice; estimates which are strongly significant. Likewise, social capital increases the chance of households seeking veterinary services, technical support, and treating their harvests. Households with members belonging to a social group have a 12 percentage point and a 14 percentage point higher chance of seeking veterinary

Table 3.12: Nearest Neighbour Matching Results of the Impact of Social Capital on Agricultural Extension and Veterinary Services

	Agric Training (1)	Agritex Visit (2)	Seek Crop Advice (3)
Social Capital	0.230*** (0.016)	0.177*** (0.015)	0.175*** (0.015)
Observations	10,645	10,645	10,645

	Seek Vet Services (4)	Tech Support (5)	Treat Harvest (6)
Social Capital	0.120*** (0.014)	0.141*** (0.014)	0.139*** (0.015)
Observations	10,645	10,645	10,645

NOTES: Average Treatment Effects on the Treated Results based on 2015 ZIMVAC data and nearest neighbor matching. The probability of treatment is based on a probit model. Social Capital is binary (=1 if a household has a member who belongs in a social group). Outcome Variables in Columns 1 to 6 are all binary. Agric Training = whether a household received any agricultural training in the 2014/2015 agricultural season. Agritex Visit = whether a household received any visit by an Agricultural Extension Officer. Seek Crop Advice = whether any member of the household sought any cropping advice during the cropping season. Seek Vet Services = whether any household member sought veterinary services. Tech Support = whether a household received any technical support during the agricultural season. Treat Harvest = whether a household treat its harvest against rodents and weevils. Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3.13: Kernel Weight Results of the Impact of Social Capital on Agricultural Extension and Veterinary Services

	Agric Training (1)	Agritex Visit (2)	Seek Crop Advice (3)
Social Capital	0.223***	0.172***	0.162***
	(0.006)	(0.018)	(0.007)
Observations	10,645	10,645	10,645

	Seek Vet Services (4)	Tech Support (5)	Treat Harvest (6)
Social Capital	0.129***	0.148***	0.146***
	(0.010)	(0.000)	(0.017)
Observations	10,645	10,645	10,645

NOTES: Average Treatment Effects on the Treated Results based on 2015 ZIMVAC data and Kernel Weighted matching. The probability of treatment is based on a probit model. Social Capital is binary (=1 if a household has a member who belongs in a social group). Outcome Variables in Columns 1 to 6 are all binary. Agric Training = whether a household received any agricultural training in the 2014/2015 agricultural season. Agritex Visit = whether a household received any visit by an Agricultural Extension Officer. Seek Crop Advice = whether any member of the household sought any cropping advice during the cropping season. Seek Vet Services = whether any household member sought veterinary services. Tech Support = whether a household received any technical support during the agricultural season. Treat Harvest = whether a household treat its harvest against rodents and weevils. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

services, technical support, and treating harvest respectively than those without; estimates which are all significant at 1 percent.

Table 3.13 above presents Kernel-Weighted estimation results for robustness check. The results confirm the findings of Table 3.12. Social capital increases the chances of households participating in agricultural training, receiving visits from agricultural extension officers, seeking veterinary services, seeking crop advice, receiving technical support and treating harvests against post-harvest losses. The estimates are not different from those in Table 3.12 and are also all significant at 1 percent. These results are also confirmed in Inverse-Probability of Treatment Weight estimation results presented in Table 3.14. Social capital increases the chances of households getting agricultural training, receiving visits from agricultural extension officers and seeking cropping and veterinary services as well as treating and preserving harvests.

Table 3.14: IPWT Results of the Impact of Social Capital on Agricultural Extension and Veterinary Services

	Agric Training (1)	Agritex Visit (2)	Seek Crop Advice (3)
Social Capital	0.229*** (0.012)	0.176*** (0.012)	0.166*** (0.011)
Observations	10,645	10,645	10,645

	Seek Vet Services (4)	Tech Support (5)	Treat Harvest (6)
Social Capital	0.131*** (0.010)	0.149*** (0.011)	0.151*** (0.011)
Observations	10,645	10,645	10,645

NOTES: Average Treatment Effects on the Treated Results based on 2015 ZIMVAC data and Inverse-Probability of Treatment Weight matching. The probability of treatment is based on a probit model. Social Capital is binary (=1 if a household has a member who belongs in a social group). Outcome Variables in Columns 1 to 6 are all binary. Agric Training = whether a household received any agricultural training in the 2014/2015 agricultural season. Agritex Visit = whether a household received any visit by an Agricultural Extension Officer. Seek Crop Advice = whether any member of the household sought any cropping advice during the cropping season. Seek Vet Services = whether any household member sought veterinary services. Tech Support = whether a household received any technical support during the agricultural season. Treat Harvest = whether a household treat its harvest against rodents and weevils. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

These results confirm hypotheses 3.3.1 through to 3.3.6. Unlike findings from Tanzania, Rwanda and Kenya by Bourne et al. (2017) where they found limited capacity for collective action, these results show that social capital and collective action have an impact on ensuring food security through agricultural extension services and minimizing post-harvest losses. Relatedly, these results are contrary to Pachoud et al. (2019) who found lack of trust and reciprocity among producers in Brazil leading to low levels of interaction and collective action. This means that in trying to understand social capital, context is very important. On the other hand, the results in general confirm Ragasa and Mazunda (2018) who found that households that receive agricultural advice have greater productivity and greater food security; and more particularly Abdul-Rahaman and Abdulai (2018) who found that participation in farmer groups is associated with increased yield and technical efficiency. Findings in this study show that social capital enhances food security.

3.6 Discussion

3.6.1 Further reflection on the concept of social capital

The definition of social capital adopted in this study requires further reflection. Defining social capital as group participation is deliberate. There is acknowledgement that measuring social capital requires different approaches that can reflect the cultural context of social capital (see e.g. Chung et al., 2014); and different levels of conceptualization (Moore and Carpiano, 2020) and that its definition and measurement are still rather unclear (Guillen et al., 2011). There is generally no agreement on the concept of social capital and it is subjective as to whether there is consistency for which dimensions of social capital are considered important for measurement (see e.g. Chung et al., 2012; Hong et al., 2007 cited in Chung et al., 2014; Jeong et al., 2021). The concept has multiple aspects, dimensions, characteristics and associations with the underlying societal context, contributing to the disagreement on its appropriateness for empirical analysis. Social participation is an important aspect of social capital in Zimbabwe as it reflects on environmental context and characteristics of its society.

Treating group membership as social capital is not entirely uncommon. The Organization for Economic Cooperation and Development (OECD), for example, includes 'trust and membership in associations' as one category of the World Value Survey that is used to measure social capital (see e.g. Chung et al., 2014; Dalton et al., 2002; Elgar et al., 2011; Mansyur et al., 2008). On the other hand, the World Bank developed the 'Integrated Questionnaire for the Measurement of Social Capital' which divides social capital into: 'groups and networks, trust and solidarity, collective action and cooperation, information and communication, social cohesion and inclusion, and empowerment and political action' (see e.g. Grootaert et al., 2004). Related, the Office for National Statistics (ONS) in the United Kingdom designed the ‘Harmonized Question Set’ that includes the following social capital aspects: social participation, social networks and social support, reciprocity and trust, civic participation and views of the local area (see e.g. Walsh et al., 2015; Webb, 2015).

There is also acknowledgement of the potential overlap of different social capital perspectives such as trust, networks, and social participation/civic engagement providing rationale for researchers to either combine available measures of these components into one social capital scale or regard one measure as a proxy for another (Moore and Carpiano, 2020). The definition of social capital adopted in this study can be viewed in this line of thinking and is closely related to the concept of group social capital introduced by Oh et al. (2004), which is the configuration of group members’ social relationships within a group and extending to the broader social structure to which the group belongs, through which essential resources for the group can be obtained.

Furthermore, this definition views social capital as a community or neighbourhood-wide construct implying that having social groups in which some household members participate is enough to generate networks, norms, and trust (see e.g. Alaimo et al., 2010). However, research on the topic is relatively sparse despite the fact that neighbourhood organizations are widely cited as mechanisms of social capital. In public health literature, inter alia, social capital has been operationalized as social participation referring to the number of groups and associations to which citizens belong (Guillen et al., 2011). Literature also points to social participation as meeting socially, helping behaviour, participation in a voluntary organization, conventional political participation and political protest behaviour (see Newton and Montero, 2007 cited in ibid). The definition of social capital adopted in this study is similar in approach to the European Social Survey which asked respondents to indicate for 12 organizations whether they “are members”, “participate actively” and/or “do voluntary work”. In the context of Zimbabwe, and with particular reference to informal social systems, social capital measured as whether a household has a member who belongs to a social group reflects the dynamism and complexity of social capital in general.

3.6.2 Limitations

The fact that only the 2015 Zimbabwe Vulnerability Assessment Committee (ZIMVAC) survey asked whether the household has a member who belongs to a social group and that other later surveys did not ask this question became a weakness in this study. This means that the study relies on one cross-sectional survey despite the fact that the ZIMVAC is an annual survey. The analysis could arguably be richer had it been possible to pool together more annual cross-sectional datasets. Even if it is not possible to identify the same households across annual ZIMVAC surveys, pooling surveys across time would improve on external validity of the findings presented in this study.

As already detailed above, the fluidity of the concept of social capital as social participation may demand a further interrogation of within-social group heterogeneity. It is logical to think that some social groups will have larger social capital endowment than others probably because of their members' influence in the overall social make-up of their group which may in turn influence household food security. There may be need for further research in which the different social groups indicated by respondents (i.e. community associations, informal savings and loans associations, burial societies) can be interrogated to show how different they are against each other in influencing food security. Furthermore, if the within-group heterogeneity causes systematic differences and is unobserved, then this is a potential source of bias that may not be fully addressed by the empirical strategy adopted in this study. The Propensity Score Matching relies on observed characteristics to assign households into treatment and control groups. There is need therefore for further studies based on empirical strategies that address unobserved heterogeneity. For example, data permitting, studies and findings based on panel data models are recommended in this regard.

For the potential challenge of endogeneity that may exist between food security and membership into various social groups, further research based on panel data models is also recommended. Empirical strategies in which the lag of social capital (measured as membership in social groups in prior years) can be used as an Instrumental Variable and this has the potential to address the problem of endogeneity. This can actually be motivated by the Arellano-Bond Estimator approach. This could not be done in this study because the ZIMVAC data does not have repeated observations on the same unit.

3.7 Conclusion

Based on Zimbabwe Vulnerability Assessment Committee data, this research assesses the impact of social capital on food security. Social capital is measured at household level and defined as a binary response as to whether a household has a member or members belonging to a social group. The research analyses the impact of social capital on a number of specific food security pillars, household hunger, coping strategies, and agricultural extension and veterinary services.

The study provides evidence supporting the importance of social capital in ensuring food security in Zimbabwe. Households with social capital are more food secure than those without in all the food security pillars outlined in the research, with all estimates being strongly significant. Relatedly, the findings show that households with members belonging to a social group are less likely to not have food to eat, to sleep at night without eating and going for a whole day and night hungry than those without social capital. Social capital reduces incidences of household hunger. Furthermore, the results show that households with social capital are less likely to skip meals, limit portion size at meal, reduce number of meals, borrow food, rely on less expensive food, harvest immature crops, send members to beg, purchase food on credit, and reduce adult consumption; than those without social capital. Households with social capital are less likely to be forced to adopt demanding and psychologically stressful food insecurity coping strategies compared to households without social capital.

Finally, the findings indicate that households with members belonging to a social group are more likely to participate in agricultural training than those without. Participating in agricultural training is important in ensuring food security. Social capital increases the household chances of receiving visits from agricultural extension officers. Interaction with agricultural extension officers is expected to increase food security through knowledge dissemination and diffusion. This kind of interaction is therefore expected to lead to increased cropping and animal husbandry advisory and technical support. The results show that households with social capital are more likely to seek cropping advice, veterinary services, and technical support than their counterparts. This should increase household food security so is preserving harvests. The results show that households with members belonging to social groups are more likely to treat their harvest than those without social capital and thereby ensure food security. The study concludes that social capital increases food security in Zimbabwe.

These results have important policy implications in that although community-based food and nutrition interventions should cater for those suffering from food insecurity, their success depends on how the intended beneficiaries evaluate the collective functioning of society. Interventions to ensure food security in Zimbabwe can ride on social groups to leverage on the benefits that members draw from their social groups, such as information sharing, learning from each other, and pooling of resources for production.

CHAPTER 4

THE IMPACT OF SOCIAL PROTECTION AND THE SPECIAL COVID-19 SOCIAL RELIEF OF DISTRESS GRANT ON HUNGER IN SOUTH AFRICA

4.1 Introduction

South Africa became the epicentre of COVID-19 in Africa (Carlitz and Makhura, 2020; Garba et al., 2020; Stiegler and Bouchard, 2020) and continues to record highest cumulative COVID-19 cases; accounting for the 90 percent of confirmed deaths in Southern Africa (see e.g. Mbunge, 2020). As a result, this prompted the authorities to institute drastic measures which include national total lockdown, curfews and stay-at-home requirements. These measures, which were the most restrictive on the African continent, have imposed huge economic costs and have negative implications for the factor distribution of income (see e.g. Arndt et al., 2020).

The severe shocks to household income and limited means to purchase food have the potential to throw households into food insecurity. Households with high dependence on labour income are more likely to experience enormous real income shock. In South Africa, the lack of food and financial resources led to ‘hunger riots’, looting and confrontation with police (see e.g. Stiegler and Bouchard, 2020). The pandemic and the lockdown measures, in general, created fear, anxiety, distress, and discomfort as well as food insecurity; all which can have long-lasting effects on well-being. Food-insecurity, for example, has long-term effects on the well-being of society and understanding its prevalence and determinants during the COVID-19 pandemic is important and can influence the creation of earmarked and effective strategies (see e.g. Kent et al., 2020).

The South African government introduced a number of temporary social and economic relief interventions, which include the Special COVID-19 Social Relief of Distress Grant of R350 per month that is equivalent to US $20, increases to existing social welfare grants, and economic support through the Special COVID-19 Unemployment Insurance Fund benefit (see e.g. Haffejee and Levine, 2020). For example, the basic Child Support Grant was increased by an extra R300 in May 2020 and an additional R500 from June 2020, which is equivalent to an additional US $26 per month per eligible child. Other grant beneficiaries (e.g. of Old Age Grant, Foster Care Grant) received an additional R250 per month. The Special COVID-19 Social Relief of Distress Grant can only be accessed by residents of South Africa who are above the age of 18 and not receiving any income, social grant or unemployment insurance benefit. The question, however, is whether these interventions have an impact on hunger given the severe shocks to incomes and the prolonged restrictive and stringent lockdown measures. This research, therefore, aims to assess the impact of social protection and the Special COVID-19 Social Relief of Distress Grant on hunger and contribute to promoting knowledge on food security in a crisis period thereby preventing the expansion of hunger during and after the social and economic crisis brought about by COVID-19 pandemic.

Based on Correlated Random Effects estimations employed on two waves of the National Income Dynamics Study – Coronavirus Rapid Mobile Survey (NIDS-CRAM), which is the first nationally representative panel data survey investigating the socioeconomic impacts of the national lockdown associated with the State of Disaster declared in South Africa in March 2020, the study offers four major findings. First, receiving a government grant reduces the likelihood of going hungry and running out of money to buy food. Receiving a government grant leads to a 6 and a 12 percentage point lower chance of going hungry and of running out of money to buy food, respectively. Second, households with individuals receiving the Special COVID-19 Social Relief of Distress Grant have an 8 percent lower chance of facing child hunger than those that do not receive the grant. Third, the results show that the Special COVID-19 Unemployment Insurance Fund benefit does not have an impact on hunger and does not cushion individuals and households from running out of money to buy food. Finally, although COVID-19 has put pressure on food security for individuals and households, there is no evidence to suggest that those who were tested or screened for the virus are more likely to go hungry or run out of money to buy food than those who were not. There is no heterogeneity emanating from being tested or screened for COVID-19 on hunger.

The rest of the Chapter is organized as follows. The next section presents short description of the special COVID-19 social protection interventions in South Africa. Section 4.3 provides a brief literature review and outlines hypotheses tested in the study. Section 4.4 details the data and methodology adopted, and Section 4.5 presents the results and discussion of the findings whereas Section 4.6 concludes.

4.2 Special COVID-19 social protection interventions

Following imminent substantial welfare losses to individuals and households as a result of its lockdown policy, the South African government responded quickly to address the adverse economic effects of the COVID-19 pandemic. On 21 April, 2020, the government allocated R502 billion (equivalent to USD 33.45 billion) towards a wide array of economic support measures for businesses and individuals of which R50 billion (equivalent to USD 3.30 billion) was ear-marked for the most economically vulnerable members of society in the form of direct financial transfers (see e.g. Bhorat et al., 2020; National Treasury, 2020), which included a temporary increase in all existing social grants (i.e. Foster Care Grant, Child Support Grant, Old Age Grant, Care Dependency Grant, War Veterans Grant, and the Disability Grant), and introduction of the Special COVID-19 Social Relief of Distress Grant.

4.2.1 Temporary increase to existing social grants

As part of the government's social grant COVID-19 intervention, the Child Support Grant amount was increased by an additional R300 in May 2020 and thereafter the figure was pegged at R500 from June to October 2020; an additional R250 monthly from May to October 2020 to all other social grants that include the Foster Care Grant, Old Age Grant, Care Dependency Grant, War Veterans Grant, and the Disability Grant. This means additional direct financial transfers to 13 million Child Support Grant and 5 million 'all other grants' beneficiaries (see e.g. K*ö*hler and Bhorat, 2020).

The Child Support Grant is a means-test social protection for children under the age of 18 given to a caregiver not earning more than R48000 a year (R4000 a month) if single and/ or not earning a combined income of more than R96000 per year (R8000 per month) if married. The child must be living with the primary caregiver and not be in the care of a state institution. The grant gives an eligible child R 440 per month and as a response to COVID-19 pandemic, the amount was increased by an additional R500 as noted above. On the other hand, the Old Age Grant is given to South African citizens, permanent residents or refugees who are 60 years or above. The recipients of the grant must meet means-test requirements and must not be maintained or cared for in an institution funded by the state (e.g. a prison, rehabilitation centre or a state old age home) and must not receive another social grant. The grant gives an eligible old person R1800 per month and due to special COVID-19 government intervention the recipient would receive an additional R250 per month for the stipulated time.

Related, recipients of the Care Dependency Grant also received an additional R250 as a direct response to COVID-19 pandemic. The Care Dependence Grant is given to caregivers of disabled children under the age of 18 upon submission of a medical or assessment report confirming that the child is severely disabled and receives permanent care or support services. The grant is means-test and the care-dependent child must not be permanently cared for in an institution funded by the state. Unlike the Care Dependency Grant, the Disability Grant is meant for disabled people aged between 18 and 59 who are certified as such through a medical or assessment report. Recipients of these grants received an additional R250 per month for the stipulated period of special COVID-19 pandemic government intervention.

4.2.2 Special COVID-19 Social Relief of Distress Grant

In response to the detrimental economic effects of the COVID-19 pandemic, the government introduced a new social grant, in the form of a Special COVID-19 Social Relief of Distress Grant, to cater for individuals above the age of 18 who are unemployed and who do not receive any income, any social grant or support from the Unemployment Insurance Fund. Furthermore, applicants must not qualify to receive unemployment insurance benefit and not reside in a government funded or subsidized institution to qualify for the Special COVID-19 Social Relief of Distress

Grant. Eligibility to access the grant extends to South African citizens, permanent residents, refugees, asylum-seekers, and special permit holders who meet the above-stated criterion. The grant gives eligible individuals an amount of R350 (USD23) per month and is expected to reach to more than 11 million beneficiaries (see e.g. Baskaran et al., 2020) that have never been catered for and the 'new poor' who have been forced to migrate from the middle of the income distribution as a result of structural changes brought about by COVID-19 pandemic. It is reported to have brought millions of previously vulnerable but unreached individuals into the social protection system (Bhorat and Köhler., 2020). Initially, the grant was meant to be for 6 months from May to October 2020 but it has since been extended by an additional 3 months to January 2021 and for a further 3 months in February 2021.

In terms of uptake, a total of 9.15 million unique applications were considered between May and September 2020 (Baskaran et al., 2020); with 73 percent of the applications made in May, reducing to 830,000 new applications in July and 195,000 in September 2020. The total number of applications reviewed on a monthly basis increased by 40 percent from May to September 2020. As of mid October 2020, more than 18.5 million COVID-19 grants were distributed suggesting that a substantial number of recipients received the grant more than once (see e.g. ibid.). The extension of the grant from November 2020 to January 2021 is estimated to have resulted in 9.8 million additional COVID-19 grants being disbursed over the three-month extension period.

4.2.3 Special COVID-19 Unemployment Insurance Benefit

The Special COVID-19 Unemployment Insurance Benefit was introduced by government to provide between 38 and 60 percent of the salary of employees who found themselves laid off specifically as a result of COVID-19 pandemic. The grant provides relief to thousands of workers who lost their jobs as a result of the toughest lockdowns that South Africa was forced to implement in order to curb the spread of the virus. The benefit covers different situations faced by employer and employees during national lockdowns as a result of COVID-19; namely illness benefit given to employees who have to self-quarantine, death benefit given in provision of death to oneself or a family member, reduced work time, and the Temporary Employer Relief Scheme. Under the Temporary Employer Relief Scheme, any employer that closes operations for 3 months or for a shorter period and suffers financial distress as a direct result of COVID-19 pandemic qualifies for the benefit. As of October 2020, a total of almost R50 billion (about USD 3.30 billion) had been disbursed in the form of benefits to 5 million workers who had been laid off.

4.3 Literature review and hypotheses

Households from developing countries with strong lockdown measures but weak social protection systems are likely to face a grim food security outlook (Arndt et al., 2020). Distribution of food parcels for the poorest communities is usually not enough under such circumstances (see e.g. Stiegler and Bouchard, 2020). The pandemic severely affects those socioeconomically vulnerable (Ribeiro-Silva et al., 2020). The health, economic, and social impacts of COVID-19 are complex, emergent and unpredictable (Lawrence, 2020). In Southern Africa, in general, the COVID-19 pandemic coincided with other existing shocks such as adverse climatic effects in Zimbabwe (Ejeromedoghene et al., 2020) and thus the coronavirus pandemic amplified the threats to food security.

The economic devastation from COVID-19 increases the importance of a robust safety net (Saloner et al., 2020). Other usual food-insecurity coping strategies such as depending on social networks for support in the form of sharing meals with neighbours and family, for example, are difficult due to lockdowns and social distancing restrictions (see e.g. Kinsey et al., 2020). The severe shocks brought about by COVID-19 demonstrate the value of having in place social protection programs that support vulnerable members of society against these unprecedented types of shocks. The following hypotheses linking COVID-19 and government grants to household hunger are advanced:

Hypothesis 4.1:

Households with individuals that receive government grants are less likely to experience hunger during COVID-19 pandemic.

Hypothesis 4.1.1

Households with individuals that receive the Special COVID-19 Social Relief of Distress Grant are less likely to experience hunger.

In general, the wide-spread stay-at-home orders and business closures instituted to fight the spread of the virus resulted in large increases in unemployment, food insecurity and hunger (see e.g. Dunn et al., 2020; Kent et al., 2020; Owens et al., 2020). The global COVID-19 has caused unprecedented job losses and financial strain (Ribeiro-Silva et al., 2020; Saloner et al., 2020)). In South Africa, a large number of workers have not been able to report for work and to earn an income during the lockdown and these also include lowly-paid workers usually engaged in the service sector, construction, manufacturing, and domestic work (Bhorat et al., 2020a). The detrimental labour market effects of COVID-19 pandemic and its associated lockdown restrictions have been disproportionately felt by individuals in lower-income households (Köhler and Bhorat, 2020). In situations like these, many individuals look up to social protection such as unemployment insurance programs as coping strategies. The impact on food security for some households will be affected in the absence of strategies to guarantee incomes. This leads to the development of the following hypotheses linking the Special COVID-19 Unemployment Insurance Fund benefit to hunger:

Hypothesis 4.1.2

Households with individuals receiving the Special COVID-19 Unemployment Insurance Fund benefit in South Africa are less likely to experience hunger.

Hypothesis 4.2

Having been screened or tested for COVID-19 increases the chances of experiencing hunger in South Africa.

4.4 Data and Methodology

4.4.1 Data

The research is based on the National Income Dynamics Study – Coronavirus Rapid Mobile Survey (NIDS-CRAM). It is the first nationally representative panel data survey that investigates the socioeconomic impacts of the national lockdown associated with the State of Disaster declared in South Africa in March 2020, and the social and economic repercussions of the global Coronavirus pandemic. The survey is aimed at informing policy based on dependable research on income, employment and welfare in South Africa, in the context of the global Coronavirus pandemic. It is implemented by the Southern Africa Labor and Development Research Unit (SALDRU). The NIDS-CRAM therefore provides a measure of how firms and families are being affected by the lockdown, the pandemic, and takes stock of the reach and efficacy of government's social and economic relief efforts.

The NIDS-CRAM is derived from a special follow up of adults from households in the National Income Dynamics Study (NIDS) Wave 5 of 2017. NIDS-CRAM is a repeated Computer Assisted Telephone Interview with two waves whose focus is on the Coronavirus pandemic and the national lockdown. Data collection for Wave 1 of NIDS-CRAM started on 07 May 2020 and ended on 27 June 2020. It interviewed 7,073 individuals. On the other hand, data collection for Wave 2 of the NIDS-CRAM commenced on 13 July 2020 and finished on 13 August 2020 after interviewing 5,676 individuals. The superiority of NIDS-CRAM lies in the fact that it is a panel survey *which tracks the same individual*; providing a window to understand and to be able to identify who is receiving new and existing grants, and what influence such receipt may have on welfare for vulnerable members of society in South Africa during trying times brought about by COVID-19 pandemic.

4.4.2 Empirical strategy

The NIDS-CRAM is a panel data with two waves and as such it allows for the adoption of empirical strategies that can deal with inherent selection bias associated with social protection programs. If individuals who choose to take up the Special COVID-19 Social Relief of Distress Grant, for example, have unique and unobserved characteristics that make them more likely to take up the grant than others then estimating the impact of the grant on food security using simple OLS estimations will result in biased results. Concerning the Special COVID-19 Social Relief of Distress Grant, Bhorat and K$\ddot{o}$hler (2020) observed that conditional on applying, certain individuals are more likely than others to be successful in their application. However, with panel data, Fixed Effects models are suited to deal with this challenge. If the unobserved heterogeneity is constant over time, with Fixed Effects, it will be differenced away and the estimate will be a true reflection of the impact of the grant on food security.

However, the variables of interest in this study are relatively constant over time given the short time difference between the waves hence using Fixed Effects estimations difference them away. It is therefore proposed to use the Mundlak's Correlated Random Effects formulation. The Correlated Random Effects allows unification of Fixed Effects and Random Effects estimation approaches. This way, it allows the inclusion of time-constant variables while guaranteeing the Fixed Effects estimates on the time-varying covariates (see e.g. Schunck, 2017). Under the Mundlak's approach, the Fixed Effects estimator can be computed either as a pooled OLS or Random Effects using the original data but adding the time averages of the covariates as additional explanatory variables (see e.g. Mundlak, 1978; Wooldridge, 2010). The Correlated Random Effects model adopted in this study is motivated as follows:

$$h_{it} = \boldsymbol{x}_{it}\boldsymbol{\beta} + \overline{\boldsymbol{x}}_i\boldsymbol{\varphi} + \boldsymbol{z}_i\boldsymbol{\gamma} + \alpha_i + u_{it} \qquad (1)$$

where h_{it} is a measure of food security for household i at time t, $\boldsymbol{x}_{it}$ captures a host of variables that influence household hunger at time t, $\overline{\boldsymbol{x}}_i$ is the average of covariates over the time periods in which a full dataset on covariates and response variables can be observed. The inclusion of $\overline{\boldsymbol{x}}_i$, mops up any correlation between this variable and the unobserved random effect. $\boldsymbol{z}_i$ captures other time constant variables, α_i is meant to account for unobserved heterogeneity, and u_{it} models idiosyncratic errors. Interest is on the estimate of $\boldsymbol{\beta}$ which captures the effect of the grants on household hunger.

Captured in h_{it} are binary outcome variables based on questions asking whether there was anyone in the household who had gone hungry in the past 7 days because there was not enough food; whether there was any child in the household who has gone hungry in the last 7 days because there was not enough food; and whether the household ran out of money to buy food in the last 30 days. Relatedly, x_{it} captures binary variables of interest based on whether the respondent or anyone in the household had been screened or tested for Coronavirus; whether the respondent received any kind of government grant; whether the respondent received the Special COVID-19 Social Relief of Distress Grant; and whether or not the respondent received the Special COVID-19 Unemployment Insurance Fund benefit.

4.5 Results and discussion

4.5.1 Descriptive Statistics

Table 4.1 and Table 4.2 show household characteristics. On average, each household is comprised of six members, two of which are under the age of 18. Five percent of the people surveyed are white, 9 percent coloured and 1 percent is of Asian origin. Of interest to note, however, is that in Wave 1 only 18 percent were living in the rural areas but in Wave 2 the figure has jumped to 28 percent. This can loosely be associated with the general trend in most countries where people temporarily migrated to rural areas in an attempt to break away from usually congested urban areas. Average household income in Wave 2 is slightly smaller compared to that observed in Wave 1 generally pointing to sustained loss of income during the COVID-19 pandemic. This is also confirmed in Table 4.3 where those who reported to be employed fell from 38 percent in Wave 1 to 10 percent in Wave 2.

Table 4.4 and Table 4.5 detail descriptive statistics for variables of interest and outcome variables respectively. In general, those that have been receiving government grants increased from 22 percent in Wave 1 to 40 percent in Wave 2 which is a reflection of a coping strategy likely to be adopted in such unprecedented situations of acute shocks where individuals are losing incomes in the face of national lockdowns. Social protection programs are therefore likely to be viewed as

Table 4.1: Descriptive Statistics – Household Characteristics

	WAVE 1 Mean (SD)	WAVE 2 Mean (SD)
Race : Black	0.85	0.86
	(0.35)	(0.35)
Coloured	0.09	0.09
	(0.28)	(0.28)
White	0.05	0.05
	(0.21)	(0.21)
Asian	0.01	0.01
	(0.10)	(0.09)
Geo area : Rural	0.18	0.28
	(0.39)	(0.45)
Urban	0.77	0.69
	(0.42)	(0.46)
Farm	0.04	0.03
	(0.20)	(0.17)
Household income	5,324.24	5,058.24
	(12,156.79)	(10,011.80)
Observations	7,073	5,676

NOTES: Standard deviations are in parenthesis. Black refers to people of specifically African origin. Asian refers to people of Asian origin including black people from Asia.

Table 4.2: Descriptive statistics – Household Size

	WAVE 1 Mean (SD)	WAVE 2 Mean (SD)
Household size	5.56	5.41
	(3.31)	(3.32)
Under 18 years of age	2.22	2.26
	(1.20)	(1.94)
Under 7 years of age	1.15	1.11
	(1.13)	(1.12)
Observations	7,073	5,676

NOTES: Standard deviations are in parenthesis.

the only fall-back. However, none received the Special COVID-19 Social Relief of Distress Grant in Wave 1 but 7 percent received it in Wave 2. Of interest, however, is the fall in those that received the Special COVID-19 Unemployment Insurance

Fund benefit from 14 percent in Wave 1 to 6 percent in Wave 2. Given the fall in those that are employed from 38 percent to 10 percent, one would expect to see an increase in unemployment benefit claim. In both the two waves, 37 percent had undergone COVID-19 testing.

Table 4.3: Descriptive Statistics – Individual Characteristics

	WAVE 1 Mean (SD)	WAVE 2 Mean (SD)
Age	40.58 (15.62)	40.86 (15.69)
Gender : female	0.61 (0.49)	0.61 (0.49)
Has tertiary education	0.34 (0.47)	0.33 (0.47)
Employed	0.38 (0.48)	0.10 (0.29)
Observations	7,073	5,676

NOTES: Standard deviations are in parenthesis.

Table 4.4: Descriptive Statistics – Variables of Interest

	WAVE 1 Mean (SD)	WAVE 2 Mean (SD)
Special COVID-19 UIF Benefit	0.14 (0.34)	0.06 (0.23)
Government grant	0.22 (0.41)	0.40 (0.49)
Special COVID-19 SRD Grant	0.00 (0.08)	0.07 (0.26)
COVID-19 test	0.37 (0.48)	0.37 (0.48)
Observations	7,073	5,676

NOTES: Special COVID-19 UIF Benefit is Unemployment Insurance Fund, which is a social protection fund that gives short-term relief to workers when they become unemployed or are unable to work during COVID-19 pandemic in South Africa. Government grant is binary based on whether the respondent received any kind of government grant. Special COVID-19 SRD Grant is the Special COVID-19 Social Relief of Distress Grant COVID-19 that can only be accessed by residents of South Africa who are above the age of 18 and not receiving any income, social grant or unemployment insurance benefit. COVID-19 Test is binary and based on a question which asked whether the respondent or anyone in the household had been screened or tested for Coronavirus.

On average, households and individuals were relatively more food insecure in Wave 1 than they were in Wave 2. This may be explained by and associated with the increase in the proportion of those that reported receiving government grants and the Special COVID-19 Social Relief of Distress Grant. From Table 4.5, 52 percent reported ever running out of money for food in Wave 1 compared to 40 percent in Wave 2. On the other hand, 26 percent reported ever going hungry in Wave 1 compared to 19 percent in Wave 2 and finally, 19 percent reported that a child has ever gone hungry in Wave 1 compared to 14 percent in Wave 2.

Table 4.5: Descriptive Statistics – Outcome Variables of Interest

	WAVE 1 Mean (SD)	WAVE 2 Mean (SD)
Ever ran out of money for food	0.52	0.40
	(0.50)	(0.49)
Gone hungry	0.26	0.19
	(0.44)	(0.39)
Child hunger	0.19	0.14
	(0.39)	(0.35)
Observations	7,073	5,676

NOTES: Ever ran out of money for food is based on a question that asked whether the household ran out of money to buy food in the last month. Gone hungry is based on a question which asked whether there was anyone in the household who had gone hungry in the past 7 days because there was not enough food. Child hunger is based on whether there was any child in the household who has gone hungry in the last 7 days because there wasn't enough food.

4.5.2 Results

Table 4.6 presents Correlated Random Effects results on the effect of government grants on household hunger. Government grant is binary based on whether the respondent received any kind of government grant. The dependent variable in Column (1) of the table is based on a question which asked whether there was anyone in the household who had gone hungry in the past 7 days because there was not enough food. Column (2) presents results on the impact of government grant on child hunger. Child hunger is binary and based on whether there was any child in the household who has gone hungry in the last 7 days because there was not enough food. Results in Column (3) of the same table are based on whether the household ran out of money to buy food in the last month.

Table 4.6: Correlated Random Effects Results on the Effect of Government Grants on Household Hunger

	Gone Hungry (1)	Child Hunger (2)	Ran out of money to buy food (3)
Government grant	-0.06***	-0.02	-0.12***
	(0.02)	(0.02)	(0.02)
COVID-19 Test	0.02	0.03	-0.01
	(0.02)	(0.02)	(0.02)
Age	-0.01	0.00	-0.03*
	(0.01)	(0.02)	(0.02)
Household size	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)
Log of household income	-0.05***	-0.04***	-0.10***
	(0.01)	(0.01)	(0.01)
Gender – female	0.01	0.02	0.04**
	(0.01)	(0.01)	(0.02)
Tertiary education	-0.05***	-0.03**	-0.05***
	(0.01)	(0.01)	(0.02)
Employed	0.07**	0.07**	0.06
	(0.03)	(0.03)	(0.04)
Geo area: traditional	-0.10	-0.03	-0.01
	(0.07)	(0.07)	(0.07)
Urban	-0.06	0.04	0.06
	(0.06)	(0.07)	(0.07)
Race: Black	0.10***	0.06**	0.09**
	(0.02)	(0.03)	(0.04)
Coloured	0.08***	0.03	0.20***
	(0.03)	(0.03)	(0.04)
Asian	0.05	-0.01	0.19***
	(0.05)	(0.06)	(0.07)
Mean: age	0.01	-0.00	0.03*
	(0.01)	(0.02)	(0.02)
Employed	-0.11***	-0.09**	-0.07
	(0.04)	(0.04)	(0.04)
Traditional	0.01	-0.04	-0.01
	(0.09)	(0.09)	(0.10)
Urban	-0.01	-0.10	-0.06
	(0.08)	(0.09)	(0.09)
Government grant	0.03	-0.01	0.07**
	(0.03)	(0.03)	(0.03)
COVID-19 Test	-0.01	-0.01	0.04
	(0.03)	(0.03)	(0.03)

	(1)	(2)	(3)
Constant	0.59***	0.35***	1.14***
	(0.08)	(0.08)	(0.11)
Observations	4,239	3,518	4,247
Number of pid	3,368	2,810	3,376

NOTES: Robust standard errors in parentheses. Dependent variables are all binary. The dependent variable for results in Column (1) is based on a question which asked whether there was anyone in the household who had gone hungry in the past 7 days because there was not enough food. Column (2) is based on whether there was any child in the household who has gone hungry in the last 7 days because there wasn't enough food. Column (3) is based on a question that asked whether the household ran out of money to buy food in the last month. Government grant is binary based on whether the respondent received any kind of government grant. COVID-19 Test is binary and based on a question which asked whether the respondent or anyone in the household had been screened or tested for Coronavirus. *** p<0.01, ** p<0.05, * p<0.1

Results in Column (1) of Table 4.6 indicate that, compared to those who do not receive any government grant, receiving a government grant reduces the likelihood of going hungry by 6 percentage points, which is significant at 1 percent. This result confirms hypothesis 4.1 hypothesizing that households with individuals that receive government grants are less likely to experience hunger during COVID-19 pandemic. As is generally expected, increasing household size by an additional member increases the chances of household hunger during crisis periods like COVID-19 pandemic era; and having a tertiary education reduces the chances of going hungry by 5 percentage points, an estimate which is significant at 1 percent. Increasing household income by 1 percent reduces the chances of going hungry by 5 percent, which is significantly different from zero at the 1 percent level of significance.

Authorities instituted drastic measures which include national total lockdown, curfews and stay-at-home requirements. The severe shocks to household income threw households into food insecurity. This is reflected in the results as those who are employed have a 7 percentage point higher chance of going hungry than those who are not employed; an estimate which is significant at 5 percent, implying that those that depend on labour income were severely affected by lockdowns. Under normal circumstances, one would expect employment status to be inversely related to household hunger. This result confirms that during lockdowns and due to the COVID-19 pandemic, people in South Africa faced hunger irrespective of employment status, with those employed bearing the greatest brunt due to income shock. On another hand, under such circumstances, vulnerable members of society are the most hard-hit. For example, blacks have a 10 percentage point higher chance of going hungry than whites in this pandemic, which is significant at 1 percent. Likewise, coloureds have an 8 percentage point higher chance of going hungry than whites, which is also significant at 1 percent.

Column (2) of Table 4.6 presents results of the impact of government grants on child hunger. The results show that there is no significant impact of receiving a government grant on child hunger. Household size is also predicted to have a significant effect on child hunger. An increase in household income by 1 percent is predicted to lead to a 4 percent lower chance of child hunger, which is significant at 1 percent. Children living with household members with tertiary education are 3 percentage points less likely to go hungry compared to those living with those without tertiary education; an estimate which is significant at 5 percent. When compared to whites, blacks have a 6 percentage point higher chance of witnessing child hunger, which is significant at the 5 percent level. COVID-19 pandemic and its associated lockdown and social distancing restrictions has had a relatively higher effect on hunger for the employed. Unfortunately, this is also affecting children as those who reported having been employed have a 7 percentage point higher chance of experiencing child hunger than those not employed, an estimate which is also significant at 5 percent.

On the other hand, Column (3) of the table shows estimation results of the impact of government grant on money to buy food. Households with individuals that receive a government grant have a 12 percentage point lower chance of running out of money to buy food compared to those without; an estimate which is significantly different from zero at the 1 percent level. This result also confirms Hypothesis 4.1 that households with individuals who receive government grants are less likely to experience hunger during COVID-19 pandemic. Estimates of the effect of household size, household income and tertiary education are all significant at 1 percent. Of interest however, is the estimated effect of gender on whether the household ran out of money to buy food. Females have a 4 percentage point higher chance of running out of money to buy food, an estimate which is significant at 5 percent. This is an important finding; reflecting gender heterogeneity in food security during the pandemic. This is an important finding considering that conditional on applying, Bhorat and Köhler (2020) found that women were less likely than men to experience a successful Special COVID-19 Social Relief of Distress Grant application. Related, blacks, coloreds and those of Asian origin have 9 percentage, 20 percentage and 19 percentage point higher chances of running out of money to buy food than whites, respectively. All the estimates are significantly different from zero at the 5 percent, 1 percent and 1 percent levels of significance, respectively.

Table 4.7 presents Correlated Random Effects estimation results of the effect of the special COVID-19 Social Relief of Distress Grant on household hunger. Results in Column (1) of the table indicate that the Special COVID-19 Social Relief of Distress Grant does not have an effect on hunger. Although it reduces the chances of running out of money for food as shown in Column (3) of the table, the estimate is not statistically different from zero. These results detailed in Column (1) and Column (3) of the table do not confirm hypothesis 4.1.1 that households with individuals receiving the Special COVID-19 Social Relief of Distress Grant are less likely to experience hunger. However, households with individuals receiving the Special COVID-19 Social Relief of Distress Grant have an 8 percentage point lower chance of facing child hunger compared to their counterpart, an estimate which is significantly different from zero at the 5 percent level. This is an important result since this may reflect hunger coping strategies adopted by households and individuals when faced with unprecedented shocks of the magnitude such as COVID-19 has caused. Households may be forced to dedicate specific social protection benefits to fight child hunger. This may reflect altruism on the part of adults during trying times. On the other hand, the results show that the Special COVID-19 Unemployment Insurance Fund benefit does not have an impact on hunger. This therefore does not support hypothesis 4.1.2 which postulates that households with members receiving the Special COVID-19 Unemployment Insurance Fund benefit are less likely to experience hunger during COVID-19 pandemic.

As for whether those that were screened or tested for COVID-19 have higher chances of going hungry, face child hunger, or run out of money to buy food, results in Table 4.6 indicate that there is no statistical difference of being screened or tested for COVID-19 on hunger. This result therefore does not support Hypothesis 4.2 above. However, to check for robustness, Table 4.8 presents results of Correlated

Random Effects with interactions, the estimate of the mean of those that were screened or tested on household hunger and on child hunger are positive and pick significance.

Table 4.7: Correlated Random Effects Results on the Effect of Covid-19 Grant on Household Hunger

	Gone Hungry (1)	Child Hunger (2)	Ran out of money for food (3)
Special COVID-19 SRD Grant	0.01	-0.08**	-0.09
	(0.05)	(0.04)	(0.06)
Special COVID-19 UIF benefit	0.07	0.07	-0.13
	(0.16)	(0.16)	(0.18)
COVID-19 Test	0.02	0.03	-0.01
	(0.03)	(0.03)	(0.04)
Age	0.00	0.00	-0.03
	(0.02)	(0.03)	(0.02)
Household size	0.00	0.01***	0.01**
	(0.00)	(0.00)	(0.00)
Log of household income	-0.05***	-0.03***	-0.11***
	(0.01)	(0.01)	(0.01)
Gender: female	0.00	0.00	0.01
	(0.02)	(0.02)	(0.02)
Tertiary education	-0.05***	-0.03*	-0.06**
	(0.02)	(0.02)	(0.02)
Employed	0.15***	0.09*	0.03
	(0.05)	(0.05)	(0.05)
Geo area: traditional	-0.15*	-0.07	-0.14
	(0.09)	(0.09)	(0.10)
Urban	-0.11	0.07	-0.03
	(0.08)	(0.09)	(0.10)
Race: Black	0.08***	0.06**	0.03
	(0.02)	(0.03)	(0.05)
Coloured	0.04	0.02	0.15***
	(0.03)	(0.03)	(0.06)
Asian	0.07	0.00	0.14
	(0.07)	(0.07)	(0.10)
Mean: age	-0.00	-0.00	0.04
	(0.02)	(0.03)	(0.02)
Employed	-0.16***	-0.11**	-0.03
	(0.05)	(0.05)	(0.06)
Traditional	-0.01	-0.06	0.17
	(0.11)	(0.12)	(0.13)
Urban	-0.03	-0.16	0.11
	(0.11)	(0.12)	(0.12)
COVID-19 Test	-0.03	-0.02	0.01

	(0.04)	(0.04)	(0.05)
UIF benefit	-0.04	-0.03	0.18
	(0.16)	(0.16)	(0.19)
Constant	0.65***	0.33***	1.18***
	(0.11)	(0.11)	(0.15)
Observations	2,034	1,690	2,037
Number of pid	1,962	1,633	1,966

NOTES: Robust standard errors in parentheses. Dependent variables are all binary. The dependent variable for results in Column (1) is based on a question which asked whether there was anyone in the household who had gone hungry in the past 7 days because there was not enough food. Column (2) is based on whether there was any child in the household who has gone hungry in the last 7 days because there was not enough food. Column (3) is based on a question that asked whether the household ran out of money to buy food in the last month. The Special COVID-19 SRD Grant is the Special COVID-19 Social Relief of Distress Grant, which can only be accessed by residents of South Africa who are above the age of 18 and not receiving any income, social grant or unemployment insurance benefit. The Special COVID-19 UIF Benefit is binary based on whether the respondent received any money from the Unemployment Insurance Benefit's Temporary Employer/Employee Relief Scheme. COVID-19 Test is binary and based on a question which asked whether the respondent or anyone in the household had been screened or tested for Coronavirus. *** p<0.01, ** p<0.05, * p<0.1

However, if anything, they should be interpreted to mean that, in general, COVID-19 pandemic has put pressure on food security in South Africa. Furthermore, the results in Table 4.8 confirm results in Table 4.6 that receiving government grant reduces the chances of going hungry and of running out of money to buy food. A household with individuals receiving government grants have a 5 percentage point and a 15 percentage point lower chance of going hungry and running out of money to buy food, respectively.

Table 4.8: Correlated Random Effects (with interactions) Results on the Effect of Government Grants on Household Hunger

	Gone Hungry (1)	Child Hunger (2)	Ran out of money to buy food (3)
(Government grant) x (mCOVID-19 Test)	-0.04	-0.02	0.05
	(0.03)	(0.04)	(0.04)
(Female) x (Mean COVID-19 Test)	-0.03	-0.04	-0.01
	(0.03)	(0.03)	(0.04)
Government grant	-0.05*	-0.00	-0.15***
	(0.03)	(0.02)	(0.03)
Mean COVID-19 Test	0.05*	0.06**	0.02
	(0.03)	(0.03)	(0.03)

Female	0.02	0.04*	0.05**
	(0.02)	(0.02)	(0.02)
Age	-0.01	0.00	-0.03*
	(0.01)	(0.02)	(0.02)
Household size	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)
Log of household income	-0.05***	-0.04***	-0.10***
	(0.01)	(0.01)	(0.01)
Tertiary education	-0.05***	-0.03**	-0.05***
	(0.01)	(0.01)	(0.02)
Employed	0.07**	0.07**	0.06
	(0.03)	(0.03)	(0.04)
Geo area: traditional	-0.10	-0.03	-0.01
	(0.07)	(0.07)	(0.07)
Urban	-0.06	0.04	0.06
	(0.06)	(0.07)	(0.07)
Race: Black	0.10***	0.06**	0.09**
	(0.02)	(0.03)	(0.04)
Coloured	0.08***	0.03	0.21***
	(0.03)	(0.03)	(0.04)
Asian	0.05	-0.01	0.19***
	(0.05)	(0.06)	(0.07)
Mean: age	0.01	-0.00	0.03*
	(0.01)	(0.02)	(0.02)
Employed	-0.11***	-0.09**	-0.07
	(0.04)	(0.04)	(0.04)
Traditional	0.02	-0.04	-0.00
	(0.09)	(0.09)	(0.10)
Urban	-0.00	-0.10	-0.05
	(0.08)	(0.09)	(0.09)
government grant	0.03	-0.01	0.07**
	(0.03)	(0.03)	(0.03)
Constant	0.58***	0.34***	1.13***
	(0.08)	(0.08)	(0.11)
Observations	4,255	3,531	4,264
Number of pid	3,375	2,817	3,384

NOTES: Robust standard errors in parentheses. Dependent variables are all binary. The dependent variable for results in Column (1) is based on a question which asked whether there was anyone in the household who had gone hungry in the past 7 days because there was not enough food. Column (2) is based on whether there was any child in the household who has gone hungry in the last 7 days because there was not enough food. Column (3) is based on a question that asked whether the household ran out of money to buy food in the last month. Government grant is binary based on whether the respondent received any kind of government grant. COVID-19 Test is binary and based on a question which asked whether the respondent or anyone in the household had been screened or tested for Coronavirus. *** p<0.01, ** p<0.05, * p<0.1

4.5.3 Discussion

The finding that households with individuals who receive government grants are less likely to go hungry and are less likely to run out of money to buy food than those without supports Arndt et al. (2020) observation that low income households in South Africa are significantly insulated by government transfer payments. This emphasizes the importance of social protection programs during severe shocks caused by COVID-19 which have a potential to throw many households into food insecurity. The finding is important because due to COVID-19 pandemic, other common food insecurity coping strategies may not be feasible. For example, social capital through sharing food with neighbours and family during lockdowns and strict social distancing restrictions is difficult (see e.g. Kinsey et al., 2020); making social protection programs one of the very few strategies available for the vulnerable.

As in many countries, food parcels were distributed to the poorest communities in South Africa, however, this was not enough (see e.g. Stiegler, 2020) further confirming the importance of government grants in helping to ensure food security during the pandemic. Government grants in general have reduced the poverty and hunger effects of the pandemic. With no extra support from the government, an estimated 9.8 million people would face hunger. Although it may be known that providing income support will reduce food insecurity, the Special COVID-19 pandemic government interventions have provided support to millions who faced destitution, especially given stringent lockdown measures, and highly strained labour markets and other income-generation activities.

However, although there is a significant impact of the Special COVID-19 Social Relief of Distress Grant on child hunger, there is no such impact on household hunger and on running out of money to buy food. This may be due to the challenges experienced in the distribution of the grant. It is reported that four months into the lockdown, 74 percent of eligible individuals had not accessed the grant (see e.g. Broadbent et al., 2020; Thebus, 2020 cited in Haffejee and Levine, 2020). Related, in August of 2020, 10.3 percent of approved applications were reported to be at the banking process bottleneck and had not been paid (Baskaran, 2020). This result somewhat corroborate the findings of Haffejee and Levine (2020) in which they concluded that the pandemic and resultant national lockdown in South Africa brought to fore shortcomings in the protection and care of children. However, their focus was on children in alternative care.

On another hand, two-thirds of the estimated individuals who received the grant in June 2020 were male despite the fact that two-thirds of individuals who experienced job losses between February and April 2020 were female (Bhorat and Köhler, 2020). The fact that 85 percent of women were found not to be eligible for the grant may explain why the intervention is not having a significant impact on hunger since elsewhere in the literature it has been observed that poor women spend most of their resources towards the family more often than their male counterparts. This may also explain why, in Table 4.6 and Table 4.8, women are more likely to run out of money to buy food and face child hunger than men.

Furthermore, there has been considerable under-coverage. According to Bhorat et al (2020b), a total of almost 6.5 million individuals in June 2020 were eligible for the Special COVID-19 Social Relief of Distress Grant but did not report receipt. These individuals will be erroneously regarded as non-recipients and therefore mask the effect of the grant on hunger. They also reported on significant differences across provinces which may explain comparative efficiencies of grant distribution systems thereby overall affecting the impact of the intervention on welfare outcomes. Another important dimension is that of ineligible recipients receiving the benefit while a lot of the eligible remain 'locked out', which may have an effect on the overall performance of the grant. According to the Department of Social Development, the Auditor General (AG) identified about 30,000 undeserving applicants who, despite not satisfying the qualifying criteria due to them receiving financial support from the government through other initiatives, were receiving the grant.

The Special COVID-19 Social Relief of Distress Grant amount of R350 per month is too low an amount and is insufficient to cover basic food costs, and is even less when shared amongst household members and this may have contributed to the result of no impact on household hunger. The grant amount is far short of the upper-bound poverty line of R 1,227 per person per month and the lower-bound poverty line of R810 per person per month. The upper-bound poverty line is the poverty line plus the average amount derived from non-food items of households whose food expenditure is equal to the food poverty line whereas the lower-bound poverty refers to the food poverty line plus the average amount derived from non-food items of households whose total expenditure is equal to the food poverty line. The Special COVID-19 Social Relief of Distress Grant amount is less than the food poverty line in South Africa, which is put at R561 per person per month. The food poverty line is the 'extreme' poverty line which is the amount of money an individual requires to get the minimum daily energy intake. The grant is only about 10 percent of the median wage in South Africa which is at R 3,300.

The finding that the Special COVID-19 Social Relief of Distress Grant has a significant impact on child hunger is an important finding. It is documented that before the pandemic, 25 percent of children in South Africa were stunted and 59 percent lived below the upper-bound poverty line (Hall and Sambu, 2016 cited ibid). Children in South Africa are vulnerable and food insecurity has long-term effects on their physical, mental and cognitive development. This means that this result has important policy implications.

The Special COVID-19 Unemployment Insurance Fund benefit, which is a COVID-19 temporary employer/employee relief scheme to provide between 38 and 60 percent of the salary of employees laid-off directly as a result of the pandemic, does not have an impact on hunger. The fact that there is no significant impact of the Special COVID-19 Unemployment Insurance Fund (UIF) benefit on hunger may point to questions of sustainability of such safety nets in the presence of unprecedented and extraordinary pressure of the form and magnitude as presented by COVID-19. This may also point to the need to further understand how individuals are enrolling and accessing the program during the pandemic.

Common problems cited in connection with accessing the Special COVID-19 Unemployment Insurance Fund benefit are that companies are having problems accessing payouts available for their employees, only some employees get payments, and foreign workers are not being paid. There have also been reports of possible fraud to the fund which resulted in investigation. For example, in September 2020, payments for the Temporary Employer Relief Scheme were ceased after investigations revealed serious irregularities that included invalid rejections and payments to ghost beneficiaries. This may explain the findings in Table 4.4. From Table 4.4, 14 percent reported receiving the Special COVID-19 Unemployment Insurance Fund benefit in Wave 1 and the figure fell to 6 percent in Wave 2. There is need for further research to understand why this is so which may in turn explain why there is no significant impact of such an important program. In the United States, Saloner et al. (2020) argued that given the closure of a number of places of business coupled with individuals' reluctance to seek in-person services due to coronavirus risk, individuals may find it difficult to visit social services offices to enrol or for customer service.

This study has a number of strengths in achieving a better understanding of the dynamics of food security during COVID-19 in South Africa. First, the survey used in this study is panel with two waves collected during the COVID-19 pandemic and as such provided an opportunity to explore the effect of social protection programs and the Special COVID-19 Social Relief of Distress Grant on food security during the pandemic in South Africa. Second, the surveys are nationally representative, which is very important given that the pandemic is not selective. This also means that the external validity of the results is somewhat guaranteed as it can be argued that the results can be generalized in the context of South African COVID-19 pandemic experiences. Related, the sample size of the two waves (N=12,749), is reasonably large and allowed the interrogation of important heterogeneity across subgroups. The size of the sample came handy when dealing with household income. The best functional form to use when dealing with household income is to consider elasticity. However, given that the data was collected during a period of unprecedented shocks as a result of COVID-19 pandemic where many households reported zero income, taking the log of income resulted in a substantial drop in the number of observations but because the sample size of the two waves was relatively large it was possible to use elasticity by taking the log of income and remain with a meaningful number of observations.

On the other hand, the study has some limitations. The National Income Dynamics Study-Coronavirus Rapid Mobile (NIDS-CRAM) surveys used in this study are computer assisted telephone interviewing surveys sampled from the National Income Dynamics Study (NIDS) Wave 5 of 2017 which means that they are likely to suffer from sample selection bias in that only those that provided mobile numbers will be covered. Sample selection bias may arise if those that were successfully interviewed were systematically different from those that were not. Related, individuals from bigger households were more likely to be sampled than those from smaller households. However, if these characteristics are fixed over time, which is strongly plausible, then it has been differenced away by the use of Fixed Effects estimations and as such the results should be a true reflection of the impact of social protection and the Special COVID-19 Social Relief of Distress Grant on hunger in South Africa.

Another limitation is that unlike the NIDS Wave 5 which asked the oldest women or most knowledgeable person in the household about the household and its members, the NIDS-CRAM asks the selected respondent questions about their households. However, the interconnectedness between the individual and the household can still be acknowledged.

4.6 Conclusion

The South African government introduced a number of temporary social and economic relief interventions. The question, however, is whether these interventions have an impact on hunger given the severe shocks to incomes and the prolonged restrictive and stringent lockdown measures. Based on the National Income Dynamics Study – Coronavirus Rapid Mobile Survey (NIDS-CRAM), which is a nationally representative panel data survey that investigates the socioeconomic impacts of the national lockdown associated with the State of Disaster declared in South Africa in March 2020, this research assessed the impact of social protection and the Special COVID-19 Social Relief of Distress Grant on hunger in South Africa.

The findings in this study indicate that COVID-19 has put pressure on food security for individuals and households. However, receiving a government grant reduces the likelihood of going hungry and running out of money to buy food. This is an important finding considering that other behavioural hunger-coping strategies usually adopted by the food insecure such as eating with neighbours and friends are not feasible during the COVID-19 pandemic due to the restrictive social distancing requirements and strict lockdowns. Furthermore, the findings indicate that households with individuals receiving the Special COVID-19 Social Relief of Distress Grant have a lower chance of facing child hunger. On the other, the Special COVID-19 Unemployment Insurance Fund benefit does not have an impact on hunger and does not cushion individuals and households from running out of money to buy food. Finally, the findings indicate that although COVID-19 pandemic has put pressure on food security in South Africa, there is no heterogeneity on hunger between those that were screened or tested for COVID-19 and those not.

These findings have important policy implications. In their entirety, government grants are a cushion to hunger during the COVID-19 pandemic. Social safety nets of this nature may be the only coping strategy available to the vulnerable during the pandemic and its associated restrictive lockdown and social distancing measures. However, it is important to pay special attention to each type of social protection and its accessibility to ensure that its effect can be maximized during times of fear, anxiety, distress and food insecurity such as posed by COVID-19 pandemic. To further understand the dynamics between social protection programs and food security during crisis periods such as posed by COVID-19 and its effects in the medium- and long-term, more studies need to be carried out to test the external validity of the findings presented herein. Furthermore, there are other food security and health aspects and measures such as nutrition and obesity that may need to be interrogated using panel data given the restrictive nature and lockdowns associated with COVID-19 pandemic.

CHAPTER 5

CONCLUSIONS

There is renewed interest in better understanding the impact of social protection on welfare in developing countries, particularly in Southern Africa due to increasing levels of poverty, devastating climate change induced suffering and collapse of family structures. It has also gained renewed prominence in the presence of unprecedented shocks such as that posed by COVID-19 pandemic. The pandemic and the associated restrictive measures such as total national lockdowns imposed severe shocks to household income throwing many into food insecurity. These desperate situations create fear, anxiety, distress, and discomfort as well as deterioration of welfare to vulnerable members of society. For many, social protection is the only available coping strategy to ensure survival.

Social protection in Southern Africa is diverse with complex and interesting dynamics characterized by, for example, formal social protection systems in South Africa, and informal initiatives in Zimbabwe that rely on traditional networks of family, neighbours and community. Both the formal and informal mechanisms aim to address deep-seated vulnerabilities through either cash transfers or social capital. This study empirically investigates the impact of social protection on welfare in Southern Africa with emphasis on South Africa and Zimbabwe. South Africa was chosen mainly because it is the only country in Southern Africa with a comprehensive formal protection system for children, the aged, disabled, war veterans and for those in need of social relief of distress; covering millions of beneficiaries. It was also chosen because it has proved to have been influential in the diffusion of social protection systems to neighbouring countries such as Lesotho and Eswatini, and it is a possible model for other relatively wealthier countries such as Botswana and Namibia.

On the other hand, Zimbabwe was selected ahead of other Southern African countries because of the relative uniqueness of its circumstances characterized by weak and in some instances absent formal systems, a majority of people eking a living outside the formal sector with irregular, uncertain incomes and little to no chance of making any contributions towards social security as well as the prevalence of informal social protection systems premised on behavioural principles of reciprocity, affective relationships, and community bonding.

The study is comprised of three papers. First, and based on five waves of the nationally representative National Income Dynamics Study (NIDS), the study assesses the impact of the Foster Care Grant on child health in South Africa. The Foster Care Grant is an unconditional cash transfer meant for vulnerable children whose families cannot provide them with a safe and nurturing environment. It is meant to provide temporary, substitute, away-from-home care to vulnerable children. Despite being comparatively generous, surprisingly the grant has not been subjected to rigorous evaluations and has not received much attention. It has been around for over 20 years, which when compared to many unconditional cash transfers in Africa, presents an interesting opportunity to better understand the long-term impact of unconditional cash transfers on child health.

Second, based on 2015 Zimbabwe Vulnerability Assessment Committee (ZIMVAC) survey data, the study investigates the impact of social capital on food security in Zimbabwe. Food insecurity is a perennial challenge for many households in Zimbabwe due to a number of potential reasons ranging from incessant droughts, other climate-change related disasters such as tropical cyclones to land tenure as well as lack of sophistication in agricultural production and little research and development. Unlike South Africa with its comprehensive formal social protection system, Zimbabwean households are forced to fall back on their informal social protection systems characterized by self organization, reciprocity, family and community ties. Households and individuals self-organize themselves in social groups ranging from community associations, informal savings and loans associations, agricultural extension groups, credit unions for inputs, and burial societies. Benefits derived from being a member in these social groups include information sharing, learning from each other, pooling resources for production; among others. The relative uniqueness of circumstances in Zimbabwe makes it an interesting case to better understand the impact of social capital on food security.

Finally, based on two waves of the National Income Dynamics Study – Coronavirus Rapid Mobile Survey (NIDS-CRAM), which is the first nationally representative panel data survey investigating the socioeconomic impacts of the national lockdown in South Africa, the study assesses the impact of social protection and the Special COVID-19 Social Relief of Distress Grant on hunger in South Africa. South Africa became the epicentre of COVID-19 in Africa and is continuing to record highest cumulative COVID-19 cases and deaths, which forced the authorities to adopt one of the most restrictive measures in a bid to contain the spread of the virus. The pandemic and the lockdown measures, in general, created fear, anxiety, distress, and discomfort as well as food insecurity.

This chapter proceeds as follows: Section 5.1 summarizes the empirical findings from the investigation of the impact of the Foster Care Grant in South Africa on child health, assessment of the impact of social capital on food security in Zimbabwe, and the impact of social protection and the Special COVID-19 Social Relief of Distress Grant on Hunger in South Africa. Informed by these findings, Section 5.2 concludes with policy implications.

5.1 Summary of findings

Chapter 2 provided an impact evaluation of the Foster Care Grant on child health in South Africa. The findings from Propensity Score Matching, Correlated Random Effects, and Hybrid models employed indicate that there is a positive and significant program intensity impact on height-for-age for children in South Africa (children aged 0-14 years), for children aged 1-4 years, and for children aged 5-9 years. However, this program intensity effect on height-for-age does not cascade to children aged 10-14 years and neither is there a significant program intensity impact on weight-for-age and body mass index for all ages.

Disaggregating by gender, the results show that there is a positive and significant program intensity impact for boys in all age categories including even children aged 10-14 years, and a positive and significant program intensity impact on weight-for-age for boys aged 1-4 years. However, there is no program intensity impact on height-for-age, weight-for-age, and body mass index for girls. On the other hand, the findings indicate that the grant has a significant program impact on height-for-age for children in South Africa; and even after paying particular attention to gender heterogeneity, there is a positive and significant program impact on height-for-age for both boys and girls. However, the program effect is not experienced by children aged 10-14 years. Overall, the Foster Care Grant has an impact on height-for-age for children in South Africa.

Chapter 3 provided an assessment of the impact of social capital on food security in Zimbabwe. The findings show that households with social capital are more food secure. Specifically, households with members belonging to a social group are less likely to engage in demanding, psychologically stressful behavioural hunger-coping strategies such as skipping meals, limiting portion size of meals, and reducing number of meals eaten. Households with members belonging to a social group have a 7 percentage point lower chance of experiencing a day with no food to eat, a 4 percentage point lower chance of going to sleep at night hungry, a 5 percentage point lower chance of limiting portion size of meals and a 5 percentage point lower chance of reducing number of meals eaten; compared with households without social capital. Furthermore, households with members belonging to a social group are more likely to seek and receive agricultural extension services than those without members belonging to a social group. For example, social capital increases the chances of receiving agricultural training, seeking crop advice, and treating harvests against post-harvest losses by 23, 17, and 14 percentage points, respectively. These results have important policy implications. For a country with weak formal social protection systems as well as recurrently experiencing climatic shocks ranging from droughts to devastating tropical cyclones, self organization, reciprocity and informal, traditional social protection systems in the form of social capital ensure food security.

Finally, Chapter 4 provided an impact evaluation of social protection and the Special COVID-19 Social Relief of Distress Grant on hunger in South Africa. In an attempt to curb the spread of the coronavirus, South Africa was forced to institute drastic and extremely restrictive measures, resulting in severe shocks to income and food security. The government then had to introduce a number of temporary social and economic relief interventions. Chapter 4 therefore answers whether these interventions introduced by government have an impact on hunger in South Africa given the severe shocks to incomes and the prolonged restrictive and stringent lockdown measures. The findings indicate that receiving a government grant reduces the likelihood of going hungry and running out of money to buy food by 6 and 12 percentage points, respectively. Furthermore, households with individuals receiving the Special COVID-19 Social Relief of Distress Grant have a lower chance of facing child hunger. However, the Special COVID-19 Unemployment Insurance Fund benefit does not have an impact on hunger and does not cushion individuals and households from running out of money to buy food. Finally, the findings indicate that although COVID-19 pandemic has put pressure on food security in South Africa, there is no heterogeneity on hunger between those that were screened or tested for COVID-19 and those who were not.

5.2 Policy Implications

The Foster Care Grant has a significant impact on stunting for children in South Africa. This is a very important conclusion for South Africa, a country with 3.7 million children who are orphaned and in need of care and where 27 percent of children are stunted. The findings show that the program contributes to the health of children but does not add to the problem of obesity that is prevalent in South Africa. This is an important finding too, considering that 13.5 percent of children aged between 6 and 14 years in South Africa are overweight and obese; a figure that is way above the 10 percent global prevalence in school children. Furthermore, the fact that there is no program intensity and program impact on weight-for-age but on height-for-age means that the program appeals to the long term human capital development as opposed to the short-term changes in nutritional status.

On the other hand, the finding that the program has no effect on children aged 10-14 years has important policy implications. Since the Foster Care Grant is awarded initially for two years with a possibility of extension for another two years, for health outcomes considerations, then preference for extension should be given to children younger than 10 years. Related, where circumstances allow, and when it does not lead to gender inequality to program access, preference for extension should be given to boys since there is no program intensity impact for girls (there is no further marginal impact for girls who receive the grant twice compared to those that receive it only once). Boys experience both significant program and program intensity impacts. There may also be need for further research to better understand why there is no further marginal impact of the program for girls and to ascertain whether this does not imply gender heterogeneity to care of foster children by foster parents.

On the other hand, the conclusion that social capital in the form of membership to social groups increases food security in Zimbabwe has important policy implications too. Interventions to ensure food security in Zimbabwe can ride on social groups to leverage on the benefits such as information sharing, learning from each other, and pooling of resources for production that members draw from their social groups. As much as community based food and nutrition interventions should cater for those suffering from food insecurity, the success of such interventions may depend on how the intended beneficiaries evaluate the collective functioning of their society. For a country with weak formal social protection systems in place, any deliberate efforts to prop-up social capital can help in improving the welfare of its people.

Finally, government grants are a cushion to hunger during the COVID-19 pandemic. Given the nature of restrictions adopted in a bid to curb the spread of the virus, they may be the only coping strategy available to the vulnerable and as such governments should ensure their continued existence. For example, the Special COVID-19 Social Relief of Distress Grant was initially for six months from May to October 2020 and was extended for another three months to January 2021. The South African government should seriously consider extending the life of the grant especially considering that it has a significant impact on child hunger. There is need, however, to pay particular attention to each type of social protection and its accessibility to minimize irregularities and ensure that its effect on welfare is maximized. To gain further understanding of the dynamics between social protection programs and welfare during crisis periods such as posed by COVID-19 and its effects in the medium- and long-term, there is need for further studies. There is scope for further studies interrogating what happens to other food security and health aspects and measures such as nutrition and obesity that may be importantly affected by COVID-19 pandemic and its related restrictive measures.

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