SOCIAL SAFETY NETS IN PRESENCE OF WEATHER SHOCKS: THREE ESSAYS ON DEVELOPMENT ECONOMICS FROM VILLAGE ECONOMIES IN KENYA

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DECLARATION

I, Silas Okech Ongudi, do hereby declare that this thesis work, submitted in partial fulfilment for the requirement of the award of Doctor of Philosophy in Economics, University of Cape Town, is my original work. No portion of this work has been submitted in support of an application for another degree or qualification of this type or in any other university or institute of higher learning. Effort has been made to ensure that where other people's work is used in support of this work, due reference or acknowledgement is made.

ABSTRACT

This thesis consists of three chapters that contribute towards a better understanding of the important role played by social safety net programs in supporting poor households mitigate the effects of weather shocks, reduce poverty and vulnerability, and increase consumption of healthy food. In achieving this, we undertake an in-depth analysis supported by econometric techniques to analyze the effect of social safety net program (in this case Hunger Safety Net Program, HSNP) on a range of outcomes, each forming a chapter in this thesis. In all the chapters, we use data from HSNP transfer collected in the four districts (namely, Turkana, Marsabit, Mandera and Wajir) of Kenya covering 2009-2012. The central theme of this thesis is to contribute towards discussion around the possibility of using social protection policies as adaptation strategy to climate change.

In the chapter two, we examine the effects of exposure to drought on child health and ask whether receipt of social safety net, in the form of HSNP cash transfer, could help poor households mitigate the negative effects of drought. Evidence from this study shows that drought experienced early in life and those measured in cumulative terms reduce a child's weight for age and height for age Z- scores by 26 and 50 percentage points, respectively. Our results further show that receipt of cash transfer seem to help households mitigate these negative effects of drought on HAZ and WAZ scores. These results provide suggestive evidence that the effects of drought might be long term in nature and that investments are necessary to cushion households against drought. This chapter contributes to several stands of economic literature. First, it extends the economic discussion on impacts of extreme weather events on child. Secondly, it contributes to the discussion on whether social safety net can help buffer the negative effects of weather-related shocks. Third, it extends the discussion on shocks and consumption smoothing in village economies. Fourth, our paper extends the discussion on the differences in gestational processes between male and female children in the developing world. Finally, our paper relates to the literature that links social safety net to climate change mitigation strategies in poor economies. The implications of our results are clear: in that large investments ae necessary in mitigating the effects of extreme weather events.

The third chapter investigates whether, for some given households, receipt of social safety net would crowd out or crowd in private transfers received from social network members, and especially when households are exposed to drought. This chapter is motivated by the paucity

of empirical evidence on how antipoverty programs affect informal transfers, particularly in poor economies where limited financial resources face competing demands from various sectors. A second motivation relates to the ambiguity of economic theory in predicting the direction and magnitude of transfer derivative (Gibson, Olivia, & Rozelle, 2011). Our result confirm evidence of per shilling crowding out when private transfers are received in non-cash forms. The crowding out effects is stronger at household compared to sub-location levels. This chapter contributes to economic literature in different ways. First, it improves our understanding on the determinants of private transfers received by households by showing that previous level of poverty and drought exposure are important factors. Moreover, it extends the discussion on how households smooth their consumption levels using private transfers. In addition, it contributes to analysis of behavioural implication of receiving public transfer on demographic compositions and characteristics of rural households. Finally, we contribute to crowding out literature by providing evidence from a developing country perspective where such information is hard to find but necessary in helping design policies that account for the socio-economic features of the rural poor in Africa.

In the final chapter, we analyze the effect of income on the consumption of nutrients amongst HSNP beneficiary and non-beneficiary households in treated and control sub-locations. This chapter is motivated by the limited empirical evidence on how temporary income impact consumption of nutrients, in instances where risk-sharing practices between communities are strong (Townsend, 1995; Fafchamps and Lund, 2003; Dercon, et al., 2012). Under such setting, the effects of social program can also accrue to non-beneficiary households through familial or community-based channels, and this has a significant effect on the design of policies aimed at reducing extreme poverty and enhancing nutritional uptakes in the rural areas of developing countries. We show that HSNP poor beneficiary households in treated sub-locations consume vitamins and minerals (specifically vitamin A, C and beta carotene) rich diets, while HSNP non-poor, non-beneficiary households in treated sub-locations consume more Vitamin A-rich diets, compared to those in control sub-locations. Further, this paper show that these effects operate through insurance and credit market channels. The implication of these findings are clear: increasing the amount of transfer received by households is likely to reduce malnutrition problem in village economies.

ABBREVIATIONS AND ACRONYMS

CCT	Conditional Cash Transfer
DFID	Department for International Development of United Kingdom
GDP	Gross Domestic Product
HAZ	Height for Age Z-Scores
HSNP	Hunger Safety Net Program
KES	Kenya Shillings
NDVI	Normalized Difference Vegetation Index
SPEI	Standardised Precipitation Evapotranspiration Index
SSA	Sub-Saharan Africa
UCT	Unconditional Cash Transfer
USD	United States of America Dollar
VCI	Vegetation Condition Index
WAZ	Weight for Age Z-Scores
WHO	World Health Organization

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DEDICATION

I dedicate this thesis to my wife Cynthia Owaga, children Eleanor Hendricks Achieng and Jectone Opondo "Tony Bidden" and my late Father Samwel Ong'udi and Mama Hellidah Ong'udi for inspiration during this PhD journey.

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CONFERENCE PAPERS

Portions of the work in this thesis have been presented in a number of international conferences. These conferences are highlighted below:

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CHAPTER 1: INTRODUCTION

1.1. Background and thesis overview

Households in rural areas of developing countries face different risks, which increase welfare costs. These risks include: volatile crop incomes due to poor yields, poor infrastructure, limited off farm employment opportunities and disjointed credit market chains. The implications of these risks are felt over a long period of time by these households and because of this, they propagate poverty and inequality. In addition, these households are ill equipped to cope with these risks and are often forced to adopt strategies that have long term negative implications, which in turn propagate further poverty and inequality. For instance, as a result of limited access to credit and conventional agricultural insurance markets due to market failures, credit constrained households often fail to purchase high return but expensive inputs. According to Boucher, Carter, & Guirkinger, (2008) and Giné & Yang, (2009), risk rationed households usually resort to low return activities for fear of losing assets. This means that households can only consume what they can afford, which often includes poor quality and unbalanced diets which increase malnutrition in these households.

In such environments, social safety net programs[1] (especially cash transfers) have been identified as optimal instruments that may help poor and vulnerable populations overcome multiple causes of poverty and rising inequalities (Ruel & Alderman, 2013).These programs started in the late 1980's with the aim to reduce the impact of shock induced poverty by transferring income and/or consumption to vulnerable households. In doing so, social safety net programs compensate for market failures (Ravallion, 2006). In recent years, the mandates of safety nets have expanded into human capital development as well as protection against social exclusion and marginalization (Devereux & Sabates-Wheeler, 2008). At the same time, interest in cash-based transfers have also increased: As of 2014, there were at least one

[1] These are non-contributory interventions aimed at transferring support (either in cash or non-cash forms) to poor and vulnerable individuals and societies to manage "... risk and volatilities and protect them from poverty and destitution". As that, they are a major component of larger social protection system which incorporates social insurance and labour market programmes. In other instances, they are referred to as either social assistance, social transfers or safety nets (World Bank, 2015: Page 7).

Unconditional Cash Transfer (UCT) in each of the 130 low to medium income countries (See World Bank, 2015 for a list of countries).

Currently, cash-based transfers are being implemented in 136 developing countries- those featured in the World Bank's Atlas of Social Protection: Indicators of Resilience and Equity (ASPIRE), and benefiting over 1.9 billion people in these countries (World Bank, 2015).[2] Although there exists heterogeneity in implementation and spending as a percentage of GDP, most programs are modelled around Mexico's PROGRESA[3] (now Oportunidades), launched in 1997. Thereafter, countries followed and set up their own versions of a safety net programs (either conditional or unconditional) before they either faded away or discontinued. The rapid growth in flagship safety net programs comes at a fiscal cost, and these costs are more pronounced in developing countries. For instance, as of 2018, the median country around the world spent on average USD 80 (or about USD 66, excluding health fee waivers) in Purchasing Power Parity (PPP) terms per person (World Bank, 2018).[4]

There are also differences in spending as a percentage of GDP. For example, low and middle income countries allocate higher share of Gross Domestic Product (GDP) to safety nets than high income countries (i.e., 1.5-1.6 verses 1.4% of GDP).[5] The weak association between the income level of a country and its safety net spending reflect differences in policy choices on portfolio of safety nets and not development levels or economic determinants. In fact, a large share (of about 0.7%) of safety net spending to GDP in low income countries are channeled to Unconditional Cash Transfer (UCT) with the exception of SSA countries (World Bank, 2015). Although most safety net programs in SSA are donor funded, the region is also home to top and low spenders globally.[6]

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[2] Out of the 1.9 billion people on social assistance beneficiary list, 44, 37 and 19 percent are recipients of in-kind donations, cash-based transfers and fee waivers respectively (World Bank, 2015).

[3] PROGRESA stands for Program of Health, Nutrition and Education and provides coverage to 5 million poor families in Mexico.

[4] In absolute terms per person annually, African countries spend about 9 times less compared to Latin America and Caribbean – i.e., PPP USD 16 verses PPP USD 158 (World Bank, 2015).

[5] However, countries affected by conflict, violence and fragile states (like in Bosnia, Burundi, Timor-Letse and West Bank and Gaza) tend to have higher share of safety net to GDP spending to foster recovery and social cohesion. In most instances, countries with higher share of spending to GDP have tended to include universal old age pensions as part of their safety net portfolios.

[6] Top global spenders in safety net as a percentage of GDP are South Sudan (10% of GDP) and Lesotho (7% of GDP) while less spenders (of about 0.2 percent of GDP) include Cameroon, Republic of Congo, Ivory Coast, Togo, Somalia, Sao Tome and Principe, Madagascar and Guinea Bissau.

1.2. Social safety nets and conditionalities

Generally, social safety net programs can be classified into: either CCT or UCT, based on attached conditionalities.[7] There are also greater diversities (especially in Latin America, Eastern Europe and Central Asian countries) in program portfolios.[8] Under CCT, beneficiaries are provided with payments (either periodic and or regular) but are required to meet some conditions or perform an activity like school attendance or health check-ups. These conditionalities are aimed at encouraging investment in human capital. As of 2015, CCT were being implemented in 64 countries worldwide, almost doubling their 2008 numbers. Although they (CCT) are not common in SSA, some of its variants are present in Burkina Faso, Cameroon, Republic of Congo, Niger, Ghana, Tanzania and Togo.

The slow growth of CCT programs in SSA can be attributed to three factors. First, there is lack of institutional capacity or weak human capital necessary for efficient functioning of CCT in SSA (Schubert & Slater, 2006). Secondly, SSA has poorly developed supply side infrastructure especially those related to health and educational interventions (de Groot, Palermo, Handa, Ragno, & Peterman, 2017). As a result, most programs are not able to cope up with increased demand arising from monitoring and enforcement of CCT. Finally, there are significant differences in context- i.e., in terms of economic and social vulnerability (Davis, Gaarder, Handa, & Yablonski, 2012). For example, in SSA, people suffer from high incidences of HIV/AIDS, persistent poverty, frequent food insecurity and high unemployment rates. Therefore, most social programmes target ultra-poor, labour constrained households and/ or those caring for orphans and vulnerable children. In other instances, programmes are forced to first target immediate survival, food security or address intergenerational poverty. This implies that improving health, nutrition and education (particularly of children) are secondary objectives.

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[7] According to Baird, de Hoop, & Özler, (2013), the difference between CCTs and UCTs is only on the level of planning, monitoring and enforcement of compliance. They identified four categories of conditionalities: 1) explicit conditions on papers with no monitoring (2) explicit conditions, monitored but with limited enforcement (3) explicit conditions with monitoring and enforcement of enrollment conditions and finally (4) explicit conditions with monitoring and enforcement of attendance conditions. They concluded that an explicit condition with compliance monitoring and penalization of noncompliance had a substantial effect on children's enrollment at school.

[8] For example, in the World Bank ASPIRE program, about 98 countries have at least four program, 33 countries have 2-3 programs while 26 countries have one or none of the types (World Bank, 2015).

In the UCT space, assistance are provided to poor households without attached co-responsibilities. These programs are dominant in SSA: As of 2015, 40 sub-Saharan African countries (out of 48 countries under World Bank's ASPIRE project) had at least one UCT programs in place (World Bank, 2015), a 90 percent growth relative to 2010 figures. In some developing countries (like Malaysia, Moldova, Vietnam and Trinidad and Tobago), cash-based transfers are part of market oriented demand side interventions that are aimed at supporting the poor and vulnerable households in their effort to mitigate against poverty and social exclusion.[9] They complement traditional supply side instruments like school feeding programs.

A major criticism of UCT is that beneficiary households are likely to spend transfer received on harmful products (like alcohol and cigarettes) at the expense of food. If this happens, transfer might have a negative effect on household nutrition, and especially those of children. However, Fiszbein & Schady, 2009; Gangopadhyay, Lensink, & Yadav, (2015) showed that receipt of safety net provide households with opportunity to shift consumption to nutritious, animal sourced diets like milk, eggs, fish and meat or to fruit and vegetables consumption. A second criticism of UCT is that they are not effective in addressing widespread poverty in developing countries. However, Baird, de Hoop, & Özler, (2013) showed that such conclusions are only possible in Latin America and when outcome of interest is improving school enrolment. This means that there are no consensus on which form of social protection is effective at alleviating poverty as results are dependent on outcome measured and study location.

1.3. Social protection policy and institutional development

Although social safety nets have existed for decades, comprehensive policies for poverty eradication started only after The Copenhagen's Social Development Summit of 1990. It took most governments about 10 years (i.e., since 2000) to start recognizing social protection as a distinct sector requiring specific policies to guide its development.[10] In terms of national policy formulation, SSA is the most active region amongst low and middle income countries (See

[9] In terms of flagship programs, cash transfers constitute 50% of safety net beneficiary rolls and therefore the largest component of safety nets globally, as of 2014. However, in terms of combined beneficiary numbers, in-kind assistance and fee waivers dominate with about 500 million people; followed by school feeding programs at 276 million people and lastly, by fee waivers and targeted subsidies with 381 million (World Bank, 2015).

[10] Of the 136 countries surveyed in World Bank's ASPIRE project, 77 countries had social protection policies in place; 31 countries are planning or formulating policies, while 28 countries had no information reported or available on policy planning (World Bank, 2015).

Table 1). As implementation of social protection involve many sectors, ordination is important to enhance efficiency.[11] However, the effectiveness of a given approach depends on the type of instrument (either social registry, beneficiary registry or monitoring and evaluation systems) in use.

Table 1: Types of social protection policies for countries with active national social protection

	Type of policy or strategy		
	Poverty reduction	**Comprehensive social safety net**	**Pure social protection**
Income group			
Low income countries	2	2	12
Lower-middle countries	4	1	16
Upper middle countries	9	9	22
Total, Middle income countries	13	10	38
Region			
East Asia and Pacific	2	1	4
Europe and Central Asia	5	1	11
Latin America and the Caribbean	3	3	11
Middle East and North Africa	4	1	2
South Asia	0	0	2
Sub-Saharan Africa	1	6	20
Total	**15**	**12**	**50**

Notes: Social protection policies incorporated under wider poverty reduction policies includes climate change and disaster risk management policies; 2) Comprehensive social protection policies encompasses social safety nets, labour market programs and pensions; 3) Pure social protection policies cover only social protection.

Source: World Bank internal monitoring reports, As at 2014 (World Bank, 2015)

1.4. Kenya's social protection space

In Kenya, social protection is entrenched under article 43 of the constitution which guarantees every person a right to social security. Social protection policies exist in two forms: either as contribution based (i.e., health insurance and social security) or non-contribution based (i.e. social assistance) schemes. They (social safety nets) target the poor and vulnerable households

[11] There exists two forms of coordination mechanism: coordination commission/committee and through lead ministry. Under lead ministry, one ministry undertakes to coordinate and lead the strategy implementation. Under coordination committee, a team is formed to coordinate and monitor commitments made by each participating institutions towards implementation of the strategy.

by guaranteeing them a steady stream of income at regular and or predictable intervals. Currently (as of 2018), social assistance expenditure in Kenya is estimated at about 2.6 percent of GDP, and is benefiting about 813,000 poor households (Partnership for African Social and Governance Research (PASGR), 2018). The growth rate of social safety net spending is estimated at 14 percent per annum between 2005-10 (Partnership for African Social and Governance Research (PASGR), 2018). Despite this, the number of poor people continued to rise by about 1.2 percent annually (between 2005 to 2015), to peak at 17.1 million (Kenya National Bureau of Statistics (KNBS), 2018).

Currently, the country operates five social safety net programs; (1) transfer to persons with severe disability, (2) hunger safety net program, (3) transfer for orphaned and vulnerable children and finally, (5) transfer to older persons. Although most of these safety net programs provide similar transfers (bi-monthly payments of about USD 20), orphans and vulnerable children had the highest expenditure (estimated at Kenya Shillings (KES) 492 million, in FY 2015/16).

1.5. Research gaps and criticism of the literature

Despite numerous theoretical and empirical contributions in the field of social protection, several important questions still remain unanswered conclusively. For instance, (i). How can a social protection programme be designed to help reduce child malnutrition under a resource constraining environment? (ii). How do social protection programs interact with private transfers received from other households as gifts or between household members not currently living in the households? (iii). Does access to income (in the form of HSNP cash transfer) increase consumption of nutrients in Kenya? A clear answer to these questions is important for two reasons. First, there is a steady rise in demand for social protection especially in developing countries. Second, most governments (especially from developing countries) face resource constraints and limited experience when it comes to implementing social protection programs. In answering these three questions, we use HSNP dataset and emphasize how exposure to drought impact our results. This is because drought is a challenge to rural household’s food security.

1.6. Description of study and data sources

To answer the three questions, we use two datasets: Hunger Safety Net Program (HSNP) phase one (2009-2012) data and monthly weather (precipitation and air temperature) data covering last 37 years (i.e. from January 1976 to December 2012).[12] These datasets have been used in economic analysis: HSNP datasets by Dietrich & Schmerzeck, (2020) to study the role of food markets in mitigating the effects of climatic shocks and weather data by Chakrabarti, (2021) to study the effects of deforestation-induced Malaria on child health in Indonesia. HSNP is a randomized controlled data collected from four districts (Turkana, Wajir, Marsabit and Mandera) of Kenya. In each district, 12 sub-locations were selected to participate in the project from a pool of all secure sub-locations. The program is currently in its second phase and is ongoing, benefiting over 100,00 households distributed across the four districts. It is a partnership project between the Government of Kenya and United Kingdom's Department for International Development (DFID) (Merttens et al., 2013). A baseline survey (or first wave) was undertaken between August 2009 and November 2010 (thereafter 2010) covering 5,108 households (of which 3,107 were HSNP poor beneficiary and non-beneficiary households residing in treated and control sub-locations). In 2011, a follow up survey was done (i.e., wave two) covering 4,637 households (of which 2,867 were HSNP poor beneficiary and non-beneficiary households residing in treated and control sub-locations). In 2012, a second follow up survey was undertaken (i.e., wave three) covering 2,436 HSNP poor beneficiary and non-beneficiary households residing in treated and control sub-locations (see Figure 2 for details). Importantly, in the third wave, 8 sub-locations (two in each district) were non-randomly dropped from the survey for security reasons. HSNP sample had low attrition rates between rounds (i.e., between 4.4 percent (wave 1 and wave 2) and 6 percent (wave 2 and wave 3)). We used different variants of these HSNP datasets (in terms of number of households) to answer the three questions that form the core of this thesis.

For historical weather data, we pool monthly average precipitation and air temperature from Centre for Climatic Research at The University of Delaware covering past 37 years (i.e., from January 1976 to December 2012) (Matsuura & Willmott, 2015). We use this weather data to construct Standardized Potential Evapotranspiration Index (SPEI) following Thornthwaite

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[12] Sources: http://microdata.worldbank.org/index.php/catalog/1917 (for HSNP data) and https://www.esrl.noaa.gov/psd/data/gridded/data.UDel_AirT_Precip.html (for weather data).

method (Thornthwaite, 1948) at 12 months' time scale to mimic local agricultural season. We identified each weather station closest to each sub-location using longitude and latitude. For localities without datapoints, we opted for the nearest available weather station data following literature recommendation (Maccini & Yang, 2009).[13] In total, there are 56 data points spread across HSNP districts: 15 in Marsabit, 9 in Mandera, 15 in Wajir and 17 in Turkana. The SPEI values are sub-location specific with positive numbers reflecting absence of drought while negative values reflecting existence of drought (McKee, Nolan, & Kleist, 1993).

Paper One: Prenatal Health and Weather-Related Shocks Under Social Safety Net Policy

This paper uses data described above to answer two age-old questions: 1) What is the effect of drought on child health? And 2) Does the receipt of HSNP transfer promote recovery of disadvantaged children? This chapter is motivated by the limited empirical evidence on the extent to which receiving a cash transfer may help buffer the negative effects of weather shocks experienced early in life, especially in Sub-Saharan Africa where rainfed agricultural production dominates. As rainfed agriculture is prone to disruptions by variation in weather patterns, it's important to understand how this is likely to influence children health in these resource constraining settings. Most previous studies have analysed the effects of weather-related shocks (like floods; drought; storm; fog) and how they affect adult labour market outcomes, ranging from mental health (Dinkelman, 2017) to education (Hoddinott & Kinsey, 2001). In addition, these previous literature have used either non-randomized datasets or studies undertaken in developed countries to tease out the effects of weather-related shocks. A third motivation originates from previous studies showing that drought exposure is likely to cause harmful effects on children's health (See Dercon & Krishnan, 2000; John Hoddinott & Kinsey, 2001). Our research is unique in that its undertaken from a developing country where weather-related shocks (in this case drought) are persistent. Also, we focus our study on children's health as opposed to previous studies that have analysed adult outcomes. Finally, it uses a randomized controlled trial to tease out the effect of drought. Our finding are clear: drought negatively affect child health, and that receipt of a social safety net (in the form of cash transfer) buffers the negative effects of drought exposure.

[13] In total, our sample covered 28 distinct weather stations out of the available 56 weather stations in the whole of HSNP districts, Kenya

This chapter therefore makes four distinct contribution to the literature on the nexus between health-nutrition and social safety nets. First, it contributes to literature on the impact of extreme weather events on household outcomes (Adhvaryu, Fenske, & Nyshadham, 2019; Almond, 2006; Banerjee, Duflo, Postel-Vinay, & Watts, 2010; Berazneva & Byker, 2017; Dinkelman, 2017; Jessoe, Manning, & Taylor, 2018; Kim, Lee, & Rossin-Slater, 2019; Maccini & Yang, 2009). Second, it provides evidence for the hypothesis advanced by Asfaw & Davis, (2018) that social safety net be used to buffer the negative effects for weather shocks. Third, it speaks to the literature on shocks and consumption smoothing in village economies. Finally, it extends the discussion on the differences in gestational processes between male and female children from a developing country's context, an area which past studies have not extensively analysed. Its envisioned that results from this piece of work will add to the literature and shape future discussion concerning these important issues.

Paper Two: How Antipoverty Programs Affect Informal Transfers: The Analysis of Crowding Out Effects in Kenya

This chapter assesses the interaction between antipoverty programs (in this case HSNP cash transfer received) and the already ungauged informal transfers with the aim of measuring the magnitude of crowding out or crowding in effects of informal transfers. The question we ask is: Does receiving a public transfer (in the form of HSNP transfer) crowd out or crowd in already engaged informal transfers? A clear answer to this question is important for two reasons. First, the existence of crowding out depicts inefficiency in resource allocation and use. Secondly, the magnitude of crowding out are large in absolute terms especially in developing countries. For instance, estimates show that between 20 to 91 percent of informal transfers are likely to be displaced as a result of implementation of public transfers in developing countries.

This assessment is therefore a response to the ambiguity of economic theory in predicting the direction of transfer derivative. A second motivation is the mixed findings from previous studies that have analysed the sign and magnitude of crowding out: these results seem to depend on the location of the study- either in developing countries or otherwise. Despite the lack of consensus on magnitude of crowding out, few studies have been undertaken using data from sub-Saharan Africa where informal transfers forms a major component of household expenditure. We bridge this gap in literature using a unique RCT dataset drawn from rural villages of Kenya where cultural norms dictate sharing of resources amongst households. We show that receipt of social benefits significantly reduce the likelihood of a household receiving non-cash transfer by approximately 6 percentage points, and lowers the actual amount received by up to 56 percent compared to baseline mean. We confirm presence of crowding out under non-cash transfer received. These results remain unchanged in presence of drought and whether a household is classified as extremely poor or otherwise.

The contribution of this chapter to economic literature are threefold. First, it contributes to understanding of the determinants of private transfers received from a developing country perspective by showing that poverty rates and exposure drought are important in understanding crowding out effects. Secondly, this research contributes to literature on behavioural implication of receiving a public transfer by showing that receipt of public transfer crowds out private transfer especially when private transfer are received in non-cash forms. Third, it contributes to the discussion around consumption smoothing to support risk pooling by confirming the importance of asset holding in smoothing consumption when households are faced with drought. Finally, this chapter contributes to the crowding out effects literature by providing evidence from a developing country perspective where such information is hard to find but necessary in helping design policies that captures all features of the rural poor in Africa.

Paper Three: Comparing Direct and Indirect Effects of Income on Consumption of Nutrients in Kenya

This chapter compares direct and indirect effects of cash transfer on consumption of nutrients in Kenya. This exercise is motivated by the fact that previous studies has focused only on the effect of social programs on poor beneficiary and non-beneficiary households (i.e., direct effects) while disregarding non-poor, non-beneficiary households (i.e., indirect effects). However, in village economies where risk-sharing practices between communities are strong (See Dercon, Hoddinott, Krishnan, & Woldehanna, 2012; Fafchamps & Lund, 2003; Townsend, 1994), the effects of social programs can also accrue to non-poor, non-beneficiary households through familial or community-based channels,[14] and this has a significant effect

[14] For instance, beyond the private cash transfers often shared with non-poor, non-beneficiary households, poor beneficiary households also host other family members who cannot afford to self-subsist, thereby increasing household sizes. This reinforces the child-fostering hypothesis, which has been shown to drive food and nutritional consumption, as well as saving rates. It is, therefore, a common practice for elderly parents (poor beneficiary households) to share a home with their adult children (non-beneficiary households)

on the design of policies aimed at reducing extreme poverty and enhancing nutritional uptakes in the rural areas of developing countries.[15] Failure to capture these indirect effects may bias the conclusions drawn from such analysis. In addition, estimates of the income elasticities of nutrition, obtained by using examples from the developing countries, are mixed: i.e., they vary from close to zero to as high as 0.54 (Bhalla, Handa, Angeles, & Seidenfeld, 2018; Brugh, Angeles, Mvula, Tsoka, & Handa, 2018; Tiwari et al., 2016). Findings from this study are that; 1) direct effects are larger than indirect effects and a rise in consumption of nutrients was primarily a result of sharing of HSNP transfers among social network members. These effects work through credit and insurance channels.

Our paper makes three important additions to the economic literature. First, it contributes to the discussion on nutrient-income elasticity[16] from a developing country perspective, where research is still limited. To the best of my knowledge, there is not study that have attempted to compare direct and indirect effects of income on consumption of nutrients using an RCT dataset and from a developing country's perspective. A paper close to ours is that of Angelucci & De Giorgi, (2009) in Mexico. However, they did not analyse the direct effects of income on consumption of nutrients and their study was also in a middle income country-Mexico. Second, our paper is linked to studies analysing the effectiveness of government aid in improving household nutrition (Angelucci & De Giorgi, 2009; John Hoddinott & Skoufias, 2004a). Our findings has implication on how poor households use social transfers: in that they spend it to improve the nutritional status of its members. Finally, our study extends the discussion on consumption smoothing in low-income countries. It is often argued that poor households tend to consume processed foods and beverages, which are generally not rich in calories (Subramanian and Deaton, 1996). Here also, we show that HSNP poor beneficiary households

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to ease care, or for richer households (HSNP poor beneficiary households) to support the children of less fortunate family members (non-beneficiary households) to enable them to attend distant schools.

[15] In HSNP districts, households share about 23.26% of the transfer they receive (i.e., KES 500 out of KES 2,150 received every two months) with neighbours, other family members and friends. The slow adoption of unconditional cash transfers (UCT), especially in Africa, can be attributed to social and economic problems such as high poverty rates, recurrent food price hikes, and the prevalence of HIV/AIDS. These challenges have two important implications: 1) they make health, nutrition, and other important outcomes secondary objectives for households; and 2) they affect program design, acceptance, scalability, cost, and impact.

[16] Income elasticity is the percentage change in consumption of nutrients as a result of a 1% change in income. This elasticity is important in understanding the determinant of nutrition and whether the social safety net is effective in promoting nutrition in poor households.

in treated sub-locations shift their consumption to diets rich in heme iron and vitamins compared to those in control sub-locations.

1.7. Contribution to related literature

This thesis contributes to economic literature, particularly in the areas of development economics, Psychology and neurobiology of poverty, public policy, health and adaptation to climate change. In the area of health and climate change, this thesis contributes to the growing literature on the effect of weather shocks on health of children. Specifically, our first paper provides evidence that exposure to drought negatively affect child's health, and that these effects are more pronounced during early years of a child's life. This information is useful because, higher proportion of households in developing countries live in rural areas and depend on rainfed agriculture for survival. This means changes in weather patterns have higher effect on livelihood support options of these people. Our second contribution relates to the construction of a multi-scalar Standardized Precipitation Evapotranspiration Index (SPEI) which meets Couttenier & Soubeyran, (2014) alternative measure of water stress. Previous studies either used single indicator of weather shock (like rainfall or its variants) to tease out the effect of extreme weather events. A third contribution relates to the analysis of the differences in gestational processes between male and female children, an area that has received relatively limited attention. Finally, our thesis contributes to the discussion around the role of social safety net as a climate change adaption strategy in poor economies.

In the area of public policy, this study contributes to the growing literature on effect of social program on the welfare of poor households. Our thesis provides conclusive evidence that receipt of non-cash transfers crowds out informal transfers received. Unlike previous studies (Gerardi & Tsai, 2014; Jensen, 2004; Juarez, 2009; Koh & Yang, 2019), this chapter also showed that the likelihood of receiving, and the amount of private transfer received is also influenced by drought and household poverty levels. This evidence is a new addition to the literature about the determinants of private transfer received, and to the best of my knowledge, have not be shown in the literature. Secondly, our findings (in paper two) confirms the importance of asset holdings in smoothing consumption in the presence of shocks. In addition, our paper is among the very few studies that look at the behavioural response of private transfers to public benefits in SSA, alongside other studies mostly conducted in South Africa (Case & Deaton, 1998; Jensen, 2004; Maitra & Ray, 2003) and Ghana (Strupat & Klohn, 2018). Third, our study contributes to understanding of the level of returns to capital from a developing country's view. In this area, previous studies (De Mel, McKenzie, & Woodruff, 2008; Duflo, Kremer, & Robinson, 2008) have found higher return to capital (of between 60 and 113 percent respectively for Kenyan shop owners and Sri Lanka micro-entrepreneurs) for existing businesses. In paper three, we find evidence of a rise in consumption of nutrients amongst indirect beneficiaries, suggesting that selection of either poor or non-poor households may not be important for a transfer to be effective.

In the development economics space, HSNP dataset allows us test the response of poor households to income changes. We find a large increase in the consumption of nutrients. Our thesis is unique here, in that, we make use of randomized controlled trial dataset as opposed to previous studies that make use of either crossectional datasets (Jappelli & Pistaferri, 2010; Krueger & Perri, 2005) or time series datasets (Subramanian & Deaton, 1996) to tease out the effect of income on household welfare. Our study is also unique in that we use experimental dataset as opposed to previous studies (Jensen & Miller, 2008) that use policy shocks to eke out the effects of shocks of welfare. However, policy shocks may operate through different mechanisms like through prices (i.e., through subsidies), may be anticipated by households (in the case of policy changes) or may be partly insured (in the case of bundled insurance products). This means that their effects might not generalize to other settings.

Finally, this thesis contributes to a growing literature on understanding the psychology and neurobiology of poverty. Recent works in this area (Haushofer, 2013; Haushofer & Fehr, 2014) have shown that the consequences of poverty may in turn affect the economic choices on poor households in an undesirable manner: in that households may be forced to reduce their consumption levels of nutritious diets. Another line of argument Dellavigna, (2009) and Haushofer & Fehr, (2014) have shown that poverty may cause stress, and this impact economic behaviour of households by increasing discount rates. Finally, Chemin, de Laat, & Haushofer, (2013) showed that a negative income shock may raise the level of cortisol hormone- which symbolizes the existence of stress. Our findings (in paper two) that extremely poor households tend to share more transfers with non-beneficiary households shows that they are also caring about other people's welfare.

1.8. Thesis outline

This thesis consists of three papers that analyses the importance of social protection policies from a developing country's perspective. These papers are organized into distinct chapters, and by adding general introduction and conclusion chapters, we end up with a five-chapter thesis. In chapter one, we provide general introduction of our thesis and highlights motivation for the study. In chapter two, we discuss how exposure to drought impact child's health (proxied by height for age and weight for age Z-scores) and ask whether receipt of a social safety net can help drought affected children recovery from such shocks. In chapter three, we analyze the interaction between public and private transfers and asks whether receipt of public transfer leads to crowding out or crowding in of private transfers. In chapter four, we compare the effects of income (from HSNP transfers) on household level consumption of nutrients. In the final chapter, we draw conclusions and summarize findings from this thesis.

CHAPTER 2: PRENATAL HEALTH AND WEATHER-RELATED SHOCKS UNDER SOCIAL SAFETY NET POLICY IN KENYA

2.1. Background and motivation

Extreme weather events and climate change linked disasters cause huge economic losses to communities. Around the world, approximately USD 144 billion was lost due to extreme weather events in 2017[17] (Swiss Re, 2019). These costs are likely to increase as the frequency and severity of extreme weather events are predicted to increase into the future especially in Sub-Sahara Africa. For instance, it is estimated that over 77 million urban poor residents will be pushed into poverty by 2030, and a further USD 404 billion incurred annually over the next 15 years to support climate adaptation (World Bank, 2016). It is unclear how long these effects will last. In the short run, however, weather-related shocks can lead to farm income loss, especially when households are not insured. In the long run, they can impact adult earnings, human capital, health and socio-economic status of women (Almond, 2006; Dinkelman, 2017; Maccini & Yang, 2009).

The reality is that it is the rural poor who bear much burden of climate change despite being not directly responsible for its causes. Dercon & Krishnan (2000) showed that poor households usually struggle to smooth consumption in presence of weather shocks. In most instances, they are forced to consume only what they produce, which often includes poor quality and unbalanced diets. This increases malnutrition, lowers farm productivity and limits possibility of better off-farm income in adult years. These challenges are magnified by credit and insurance market imperfections which prevent poor farm households from purchasing high return but expensive inputs. At household level, it is the children (those aged within 0-5 years) who suffer most from climate shocks[18]. This is because children not only have less developed immune systems that make them more vulnerable to sudden weather and climate changes, but they also exhibit high nutritional requirement during early stages of their growth (Martorell,

[17] Approximately 63.7 percent of these losses are due to hurricanes especially Harvey, Maria and Irma.
[18] In Sub-Saharan Africa (SSA) alone, for instance, over 58 million children are classified as malnourished and a total of USD 25 billion is lost in productivity and gross domestic product due to chronic malnutrition (UNICEF, 2019).

1999). Therefore, it is important to provide evidence that depicts the relationship between weather shocks, health and malnutrition from a developing country context to foster policy interventions that are more efficient and tailored to the socio-economic characteristics of poor and malnourished households.

In this paper, we extend the economic discussion on impacts of early life shock on child health. In particular, we present result from Hunger Safety Net Programme (hereafter HSNP) implemented in Turkana, Mandera, Marsabit and Wajir districts (counties since 2013), Kenya. HSNP is an unconditional cash transfer that aims at reducing poverty, improving asset accumulation and increasing food and nutrition security in Kenya. This is done by providing regular transfer of Kenya shillings (KES) 2,150 (approximately USD 20)[19] to each beneficiary household every two months[20]. The amount is equivalent to 75 percent of the World Food Program food aid ratio which was operating in the region in 2006. During the first phase of its operation (2009-2012), the program targeted 60,000 households in 48 sub-locations[21] in the four districts of Kenya (Merttens et al., 2013). We examine the effect of drought on child health (proxied by HAZ and WAZ scores) and ask whether HSNP can promote recovery of disadvantaged children.

We focus on malnutrition for at least three reasons. First, evidence have shown that malnutrition has long lasting negative implications on health, especially among children and female groups (Alderman, Hoddinott, & Kinsey, 2006; Martorell, 1999). It reduces children's cognitive development which in turn negatively affects their learning outcomes and human capital development (Grantham-McGregor, Walker, Chang, & Powell, 1997; Johnston, Low, de Baessa, & MacVean, 1987). Malnutrition is furthermore responsible for over a half of under five children deaths in developing countries and it leads to deficient physical and mental health. For instance, malnutrition-related diseases (like anemia) increase healthcare costs, which in turn promote poverty and inequality. Second, despite some progress observed in some countries (See Table 2), the burden of malnutrition is still unacceptably high. Finally, malnutrition increases socio-economic losses and lowers Gross Domestic Product (GDP) of a

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[19] USD 1 = KES 103.8 (Exchange rate as at September 2019)
[20] The value of HSNP transfer was increased to KES 3000 in September/October 2011 (payment cycle 16) and further to KES 3500 in March/April 2012 (payment cycle 19). The program also made a once off payment in July/August 2011 because of severe drought to support coping mechanism
[21] A sub-location is the smallest administrative unit consisting of about 200 households living close to each other and is headed by assistant chief, assisted by local leaders.

given nation. Specifically, malnutrition is responsible for over USD 25 billion loss of productivity and Gross Domestic product in developing countries (UNICEF, 2019). This limits the possibility of achieving a number of sustainable goals by 2030, and in Africa it jeopardizes the aspirations included within the agenda 2063.

Our analysis provides important findings that contribute at improving the understanding of the nexus drought-health-malnutrition. First and foremost, we found that exposure to drought worsens child health especially height for age and weight for age Z-scores. Quantitatively, a one-year exposure to drought during in-utero period reduces a child's WAZ scores by approximately 0.11 standard deviations. Moreover, we show that exposure to cumulative drought reduces a child's HAZ scores by 0.01 standard deviations. Comparatively, exposure to cumulative drought (between and including 0-5 years) had a negative and significant effect on height for age z-scores while drought exposure during in utero period had a significant effect on WAZ scores. On whether receipt of HSNP remedies these negative effects of drought, our results find evidence of possibility of remediation for cumulative drought and on HAZ scores. In addition, we find possibility of remediation for drought experienced during in-utero period and on WAZ scores. As a comparison, we note strong evidence of possibility of remediation when HSNP is measured as a dummy compared to the number of months of exposure. This implies that investments aimed at improving early life conditions should target in-utero period for better returns and promotion of catch up growth for children in poor households. These findings speak to the need for effective targeting of poor households to ensure benefit of social programs accrue to only these households for improved outcomes and reinforce the potential offsetting effect of these transfers in improving the conditions of recipients. Finally, we show that female children are more affected by early life shocks, especially drought, than their male counterparts and provision of social safety net does not seem to buffer the effects of drought in general. This finding highlights the need for more attention on pregnant mothers, and this can be through promoting consumption of nutritious diets. Also, it is important to support social welfare systems that prevent weather shocks from occurring or from being translated into absolute deprivation.

This study makes several contributions on the existing economic literature. First, our paper contributes to an active literature on the impact of extreme weather events on household outcomes (Adhvaryu et al., 2019; Almond, 2006; Banerjee et al., 2010; Berazneva & Byker, 2017; Dinkelman, 2017; Jessoe et al., 2018; Kim et al., 2019; Maccini & Yang, 2009). Unlike most previous literature that focused on adult outcomes, our paper looks at infant health. This allows us to supplement the existing literature and shed more light on how weather shocks affect nutrition at a younger age. In addition, we use randomized controlled experiments unlike previous studies that relied on non-experiments to show the effect of shocks on adult outcome.

Second, our paper also extends the discussion on whether social safety net can buffer the negative effects of weather shocks, an area that has received very little policy attention. Most of the related studies have either used precipitation (Adhvaryu et al., 2019; Maccini & Yang, 2009) or extreme temperatures (Jessoe et al., 2018; Kim et al., 2019) to capture weather variation and drought. This is despite the fact that using a single indicator as a measure of drought assumes other variables are either stationary or are not important (Couttenier & Soubeyran, 2014). This implies that occurrence of drought is due to temporal variation in precipitation only which is inconsistent with previous literature findings (Couttenier & Soubeyran, 2014). In this paper we overcome this limitation by using a multi-scalar Standardized Precipitation Evapotranspiration Index (SPEI) which is an alternative measure of water stress recommended by Couttenier & Soubeyran, (2014). This index combines multi-time scale aspects of Standardized Precipitation Index (SPI) with evapotranspiration, hence its suitability for climate studies. In addition, SPEI results are consistent with climatic model's prediction of rising global temperatures in the past 150 years (IPCC, 2007; Jones & Moberg, 2003).

Third, our study speaks to the literature on shocks and consumption smoothing in village economies. Although this literature has grown since the seminal work of (O. Attanasio & Ríos-Rull, 2000; Cochrane, 1991; Deaton, 2003; Kochar, 1999) there seems to be no uniformity in findings. For instance, whereas some studies found evidence of consumption smoothing (Garcia, Moore, Garcia, & Moore, 2012; Gilligan & Hoddinott, 2007), others have found no or limited empirical support for consumption smoothing (Dercon & Krishnan, 2000; Porter, 2012). A common feature worth noting in these papers is the non-application of exogenous source of variation. In this paper, we overcome this limitation by constructing an exogenous index accounting for locality specific precipitation and temperature in the last 37 years.

Fourth, our paper extends the discussion on the differences in gestational processes between male and female children in the developing world. Specifically, we test the fragile male hypothesis of intra-uterine development which past studies have not extensively analysed. Our results mirror those of Clark, D'Ambrosio, & Rohde, (2019) who showed that male children were more vulnerable to shocks in terms of reduced birth weight than their female counterparts.

Finally, our paper relates to the literature that links social safety net to climate change mitigation strategies in poor economies. Asfaw & Davis, (2018) and Lawlor, Handa, & Seidenfeld, (2017) showed that social safety net recipients are able to mitigate the negative effects of weather shocks. In India, Ajefu & Abiona, (2018) confirmed these shock cushioning patterns of a social safety net in presence of drought. Our results support previous findings on stunting and underweight under cumulative drought measure, which reaffirm the notion that social transfer is an important component of climate change adaption strategy in poor economies. Our paper is similar in spirit to Dasgupta, (2017), but we extend it by using a superior indicator of drought (SPEI) than her measure of drought – Standardised Precipitation Index, which is based on precipitation only and is therefore in contrast with climatic model's prediction concerning global temperatures.

The remainder of the paper is structured as follows. Section 2 provides a brief description of HSNP and the key identification strategies. Section 3 describes malnutrition prevalence in Kenya and Africa in general. Section 4 explains data sources while section 5 provides a discussion of the theoretical framework that guides our study. Section 6 discusses our estimation strategy followed by results and findings of this study in section 7. Finally, in section 8, we provide a brief conclusion and some important policy recommendations.

2.2. The unconditional cash transfer program and experimental design

Hunger Safety Net Program (HSNP) is a government run, donor funded program launched in 2009 in Turkana, Mandera, Marsabit and Wajir districts (now counties) of Kenya. This program is aimed at alleviating poverty, improving asset accumulation and food security in Northern Kenya (See Beesley, Brady, & Laura, n.d. and Merttens et al., 2013). In its first phase (2009-2012), HSNP transfer (about USD 20 every two months) was approximately 12 percent of beneficiary household consumption expenditure. All payments were made through biometric smartcards provided by local financial institution or its appointed agents. To factor in the inflation cost, the transfer amount was increased to USD 30 and further to USD 35 in 2011 and 2012, respectively (Merttens et al., 2013). A unique feature of this program is its emergency contingent transfer fund which cushions households against extreme or severe drought conditions. Approximately 70 percent of households are poor beneficiaries for this fund if they experience severe or extreme drought.[22] Specifically, when Vegetation Condition Index (VCI) indicates severe (extreme) condition, HSNP scales its transfer to 50 percent (75 percent) of all registered households (Merttens et al., 2013).

The program used three different targeting criteria: (1) community-based targeting (CBT), (2) social pension and (3) dependency ratio, in selecting households for inclusion. A household could get more than one transfer depending on member composition[23]. It is important to highlight that although the program was pro-poor based on its geographical location, only transfers driven by CBT meet poverty criterion. The selection of HSNP districts was based on poverty levels calculated from Kenya Integrated Household Budget 2008/09 Survey. Within the four districts, 48 program sub-locations were selected randomly from a pool to resemble each other (treated and control) for ease of comparison. The sub-locations were randomly assigned to either treatment or control through lottery attended by HSNP officials, district administrators and local leaders. Households were considered treated if they lived in a treated sub-location and received a transfer. During the first phase (2009-2012), control households did not receive HSNP transfer and were not either informed whether they would receive HSNP transfer in future to prevent priming effects.[24] It is important to note however, that control households started receiving HSNP transfers in 2013 (in the second phase of HSNP), covering 2013-2019. In the first phase (for which we have the data), detailed information of the children was collected in 2009 and in 2012 (3 years after baseline). In these two periods, children (those between 0-5 years) were not uniquely identified. In addition, dropping of 8 sub-locations (two in every HSNP district) significantly affected the randomization process of the survey. The current analysis uses variation in the participation into the program across all four districts to identify the impact of receiving HSNP transfer on child nutrition in presence of drought.

[22] Drought is measured using VCI which compares current normalized differenced vegetation index to past values in a given region. A low index value indicates a bad state of vegetation or condition and vice versa.
[23] For instance, a household could have a sick of old person while at the same time there is a member who is retired and has reached a recommended minimum age of 65 years. In such a situation, a household received two transfers: one for social pension and other for the dependency requirement.
[24] Priming involves using cues to engage participants in a task with an intention to influence their decision. It therefore has the potential to influence thinking, behaviour and actions towards subsequent activity.

2.3. Prevalence of malnutrition in Africa

Malnutrition is a major health concern in developing countries, especially in sub-Saharan Africa (SSA). Specifically, over 20 percent of its children and young women are considered malnourished. SSA is one of the regions in the world where stunting increased between 2000-2018. Table 2 below shows trends of stunting in Africa. Results show that the southern part of Africa had the lowest prevalence of malnutrition over the entire period partly due to stability recorded in most member countries in this region. In fact, countries that are frequented by civil wars or droughts (Eastern and western Africa) have reported a rise in stunting although the magnitude of this rise varies considerably.

Table 2: Prevalence of stunting in Africa (Number of people affected, in millions)

Regional groupings	1990	1995	2000	2005	2010	2015
Eastern Africa	19.2	19.8	21.5	22.7	23.5	23.9
Middle Africa	5.9	6.5	7.0	7.7	8.6	9.2
Northern Africa	6.1	5.5	4.9	4.7	4.8	5.1
Southern Africa	2.1	2.1	2.0	2.0	2.0	2.0
Western Africa	13.2	13.9	14.9	16.1	17.2	18.2
Africa	**46.4**	**47.8**	**50.3**	**53.2**	**56.0**	**58.3**
Global	**252.5**	**221.4**	**198.2**	**183.0**	**170.7**	**157.2**

Source: UNICEF/WHO, (2019)

The region is also a home to vitamin A and iron deficiencies, which negatively impact child growth and development. For instance, between 2000-2018, an additional 1.4 million children in Eastern and Southern Africa and a further 6.5 million children in West and Central Africa were classified as malnourished (UNICEF, 2019). Malnutrition is caused by high levels of poverty, rising cost of living and globalization. These factors promote overdependence on monotonous diets of tubers and cereals at the expense of nutrient dense fruits, vegetables and animal rich diets.

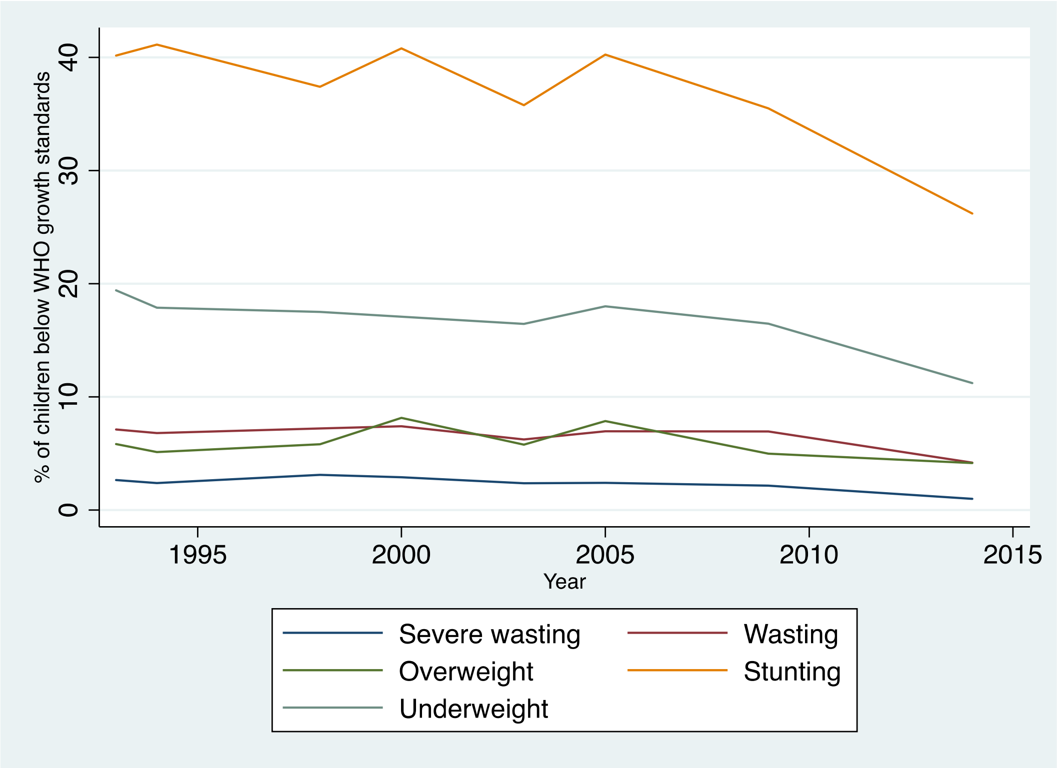

Figure 1: Evolution of malnutrition indicators in Kenya

NOTES: Severe wasting captures the percent (%) of children below <- 3 standard deviations from medium weight-for-height (WH) of World Health Organization (WHO) child growth standards; Wasting and Overweight capture the % of children below <-2 standard deviations from medium WH of WHO child growth standards; Underweight and Stunting capture the % of children below <-2 standard deviations from the median weight-for-age and height for age of the WHO Child Growth Standards respectively.

Source: UNICEF/WHO, (2019)

In Kenya, the situation of malnutrition is not different. For example, over 26% of the population are classified as stunted although there is a declining trend in child growth standard measurement indicators (Figure 1). Moreover, prevalence of under 5 stunting in Kenya - estimated at 26.2%, exceeds those of developing countries average by almost 1.2%. In terms of wasting prevalence, developing countries figures double those found in Kenya depicting the possibility of achieving global targets. The country suffers from over and traditional malnutrition. Estimates indicate that 10 percent of rich households consume 3,330 compared to 918 calories per day consumed by poor households. The burden of malnutrition constrains achievement of almost all the sustainable development goals (SDGs), and it is also a violation of human rights. There are two major channels through which drought exposure affects health of children: direct and indirect mechanisms. The direct channel works through limiting household access to clean water in presence of drought. These increases contact with disease causing organisms which in turn limit absorption of micronutrients. The second channel or the indirect channel works through negative income shocks. As a result of exposure to drought, households lose assets (such as livestock or crop yields) which results in increased prices. This in turn increases household consumption expenditure or reduces consumption of healthier diets, thereby increasing malnutrition. This indirect mechanism is the focus of this study.

A possible solution to malnutrition challenge is to increase level of investment in child health especially during the first 1000 days of life. This is plausible because estimates show that a dollar return from investing in child nutrition during the critical window (first 1,000 days) results on average USD 45 (UNICEF, 2019). In line with this, the use of social safety net has received much policy attention due to its cheap initial cost, perfect targeting of poor households and its local economy-wide impacts.

2.4. Data

2.4.1. HSNP data

Our data for this study is from two sources: the Hunger Safety Net Program survey[25] collected in 2012 and weather data covering 1976-2012 from University of Delaware Centre for Climatic Research.[26] HSNP household survey was carried out by Oxford Policy Management in collaboration with the Government of Kenya, covering four arid and semi-arid districts: Marsabit, Mandera, Wajir and Turkana, in Kenya. HSNP districts experience bi-modal rainfall patterns with long and short rainy seasons equally spread throughout the year. The prevalence of wasting and being underweight in these districts is high. About 25 percent of children are classified as malnourished, far above national averages[27] (KNBS & ICF Macro, 2010). There are serious cases of stunting which affect over 30.2% of children (Table 3). Most households are income poor[28] and practise nomadic pastoralism as a source of livelihood. Frequent and widespread drought is responsible for annual livestock deaths and deterioration of food and nutrition situation in HSNP districts. For instance, in the last two decades, more than 10 cases

[25] Source: http://microdata.worldbank.org/index.php/catalog/1917
[26] Source: https://www.esrl.noaa.gov/psd/data/gridded/data.UDel_AirT_Precip.html
[27] In the rural parts of Kenya, about 37 percent of children are classified as stunted, 17 percent underweight and 7 percent as wasted (KNBS & ICF Macro, 2010)
[28] The monthly average income of households in HSNP sub-locations (treated and control) ranges between KES 965.45-1,163.75 per month against the national average of KES 6,088 per month for rural households respectively (KNBS, 2018).

of drought were reported in the HSNP districts, and this resulted in asset losses, population displacement and food price hikes.

The questionnaire used to collect HSNP data was administered to household heads by trained enumerators and covered demographic, social and economic information at household and community level. It also contained detailed child specific information such as age (in years) at the last birthday, weight (kilograms), height (centimetres). Additional questions referred to whether child measurement was taken while standing or lying down, whether a child is a joiner, school attendance, birthplace, among other questions. In the three HSNP surveys (2009/10 (thereafter 2010), 2011 and 2012), information on children were only collected in 2009 and 2012 surveys. In this study, however, we use only a 2012 survey, approximately two years after the launch of HSNP in Kenya.

In the 2012 survey, information was collected from 1,543 children distributed across the four HSNP districts and treatment category: either as HSNP treated or control sub-locations (see Figure 2 for calssification). From this sample, we dropped 203 observations (13.2% of the sample) because of incomplete information occasioned by mothers' refusal to participate or non-availability at the time of the survey. Out of the remaining 1,340 children, four observations were dropped because they had similar unique identifiers making it hard to distinguish them. The final sample consists of 1,336 children distributed equally amongst the four HSNP districts and between treated and control groups. To capture HSNP participation, we created a dummy variable which equals one if a child resides in a household selected to receive HSNP transfer (treated household) and zero otherwise. As a starting point, we ran a regression with all HSNP poor beneficiary households in treated and control sub-locations akin to estimating intention to treat effects (See figure 2 for HSNP household classification). In further analysis, we also ran similar regression but limited our dependent variables (i.e., HAZ and WAZ scores) to absolute value of 6 standard deviations.[29] This procedure is motivated by World Health Organization (WHO) findings that values outside absolute value of 6 standard deviations are unreasonable and are likely caused by measurement errors (WHO, 2011).

[29] This restriction resulted in droping of about 4.79 and 0.15 percent of HSNP children under HAZ and WAZ scores, respectively.

As a robustness check, we followed and used a continuous measure of exposure, the self-reported number of months of exposure to HSNP transfer for those households that received HSNP transfers (Dasgupta, 2017). This information is only reported by households in treated but not in control sub-locations. For households in control sub-locations, the number of months of exposure to the HNSP transfers is zero. In instances where a treated household failed to report the number of months of exposure, we used the maximum locality specific average number of months of exposure, based on the reported month at which this locality started receiving HSNP transfer. Although most of the variation can be considered location specific, some households experienced technical problems or were not available in some months due to their nomadic pastoralist lifestyle. The variation in months of exposure seems to be a good measure of treatment for robust testing of our result, as suggested in Dasgupta, (2017). In summary, this measure captures the differences in exposure length across sub-locations in terms of treatment and control.

Using this information, we calculate child health indicators: height for age and weight for age z-scores. We also constructed child, household and community level variables used as controls in our analysis. We merge this information with region specific precipitation index generated from rainfall and temperature data covering 1976-2012 in a 12 months' time period.

2.4.2. Weather data and shock estimation

In Kenya, 90 percent of the rural households are small-scale farmers who depend mainly on rain for crop production. HSNP districts are no exception. To construct an exogenous measure of drought exposure, we use historical weather (precipitation and temperature) data from Terrestrial air temperature and precipitation: 1900-2014 version 4.01 provided by the University of Delaware Centre for Climatic Research (Matsuura & Willmott, 2015). This data is gridded on 0.5 by 0.5 degree resolution (or 56 by 56 kilometres) around the equator. We have information on the monthly minimum and maximum temperature and mean precipitation levels for every point and month-year covering all periods (January 1976 to December 2012). Specifically, we use monthly data from 1976 to 2012 in constructing Standardized Potential Evapotranspiration Index (SPEI) at 12 months' time scale to mimic local agricultural season (see Appendix 2.7 and references therein for additional information on calculation). We follow the common practices recommended in the literature and consider a minimum of 30 years when constructing SPEI. Using SPEI has several merits; it is superior to other drought indices like Standardized Potential Index (SPI) used by Dinkelman (2017) and the Palmer Drought severity

Index. It is also a form of alternative measure of water stress, recommended by Couttenier & Soubeyran, (2014) for identifying drought events.

We first decoded this data using geospatial software (QGIS) and aggregated locality specific monthly weather data using closest longitude and latitude. Using this decoded weather data, we applied the Thornthwaite method (Thornthwaite, 1948) in constructing potential Evapotranspiration (ET_0) because of the small differences between minimum and maximum temperatures from our 56 data points (15 in Marsabit, 9 in Mandera, 15 in Wajir and 17 in Turkana districts) (see appendix 2.8 for details). This fits well with Thornthwaite method which is appropriate under such limited settings. We then merge the constructed SPEI values with HSNP child data using the name of sub-location where a household resides and a child's birth year and month. For localities without rainfall datapoints, we opted for the nearest available weather station data following literature recommendation (Maccini & Yang, 2009).[30] This is possible because, HSNP districts usually receive similar rainfall patterns all year round and are geographically close to each other. Given that climatic data is also captured over 56km by 56km radius, it is a good approximation of the local conditions. Using this merged SPEI and HSNP child dataset, we define drought in a given locality and year, as an indicator variable taking the value of one if SPEI is less than -1.5 and zero otherwise (McKee et al., 1993). Our initial starting point is one year (or 12 months) before the reported birth year (what we call in-utero period) up to and including age 5.[31] At each of these years (from in-utero to age 5), we created a dummy variable using SPEI and aggregated these dummies to form cumulative drought measure.

We captured drought exposure using two variables. First, we used a dummy variable which equals one if a child was exposed to drought during in-utero period only. We chose to concentrate on this critical window because previous studies have shown that during this time, the human body requires more nutrients and might be affected by its insufficiency occasioned by drought (Martorell, 1999). The second measure of drought is the cumulative drought

[30] In total, our sample covered 28 distinct weather stations of the available 56 weather stations in the whole of HSNP districts, Kenya.

[31] Our definition of in-utero period cover the entire 12 months before a child's birth. This means that our definition includes three additional months prior to pregnancy.As Rocha and Soares (2015) showed, a child's health endowment can be influenced by his mother's health before conception.

exposure variable measured as the total number of droughts a child is exposed to from in-utero up to and including age 5 (Dinkelman, 2017).

We exploit two features of our data in the empirical analysis. First, is the random variation in exposure to local drought by children of different birth cohorts and localities. This exogeneity provides us with a convincing variation which allows for comparison of drought exposure on child health for children who were more or less exposed to drought in their locality of birth controlling for other covariates. Using cumulative drought measure allows for the inclusion of separate natural experiments in the identification of early life shock across different years and localities. This eliminates concerns arising out of fear that our results might be impacted upon by confounding shocks to child health associated with a single drought event. The second feature we exploit is the perfect randomization of HSNP localities and the staggered introduction of sub-locations into HSNP participation over the 12 months period. At every period, two sub-locations (treated and control) were randomly chosen for inclusion into the program simultaneously and this procedure was also replicated during follow up surveys. This allows for comparison of treated and control households without worrying about any selectivity problem arising from participation.

2.5. Theoretical framework

Many different challenges are associated with the prevalence of malnutrition, including delays in motor development among children, increase in the likelihood of disease infection, lowering of cognitive ability and earning potential in later life (Alderman et al., 2006; John Hoddinott & Kinsey, 2001; Müller & Krawinkel, 2005). Past evidences link high prevalence of malnutrition in rural areas to the changing weather patterns which (in) directly affects food production. This in turn impacts the type of investment that parents make about children's health. To model child malnutrition, we follow Grossman's model of healthcare outcomes (Grossman, 1972; Maccini & Yang, 2009) but extend it to include receipt of HSNP transfers. Under this model, healthcare is a durable capital stock which is used in producing desired health outcome.

As a starting point, assume an individual who decides on the amount of investment to be made in health to maximize her utility. This decision is moderated by socio-economic, demographic and environmental factors. This relationship can be mathematically represented in a health production function as shown below (Equation 1.1).

$$H_t = f(H_0; N_1 \dots N_t; X; C_0, C_1 \dots C_t; D_0, D_1 \dots D_t; HSNP_i) \quad (1.1)$$

In this function (Equation 1.1), the health status of a child in a given time period t (H_t) is determined by his initial stock of health (H_0), history of health interventions or inputs like diet counselling $(N_1 \dots N_t)$; history of health infrastructure available in the community $(C_0, C_1 \dots C_t)$; time invariant demographic characteristics (such as age and gender) of a child (X). Other factors of interest might include, existence of disease enhancing environment like droughts or floods $(D_0, D_1 \dots D_t)$. As a result of the negative effect of drought, households may receive a transfer from government or development partner in the form of a social safety net to cushion themselves $(HSNP_i)$ or otherwise.[32] As this is income to households, it is likely to increase consumption levels, and this indirectly influences nutritional status of its members.

A child's initial stock of health (H_0) is influenced by early life environmental conditions (R_0) she is exposed to. Studies have shown that these environmental conditions, especially drought, occurring early in life negatively influence health outcomes (Maccini & Yang, 2009). Other important factors that have been shown to influence a child's initial stock of health include the availability of community infrastructure (C_0), disease enhancing environment (D_0) and the genetic characteristics of a child (G). These determinants are summarized below (Equation 1.2).

$$H_0 = k(G, R_0, C_0, D_0) \quad (1.2)$$

By combining these two equations, we obtain a theoretical framework detailing the extent to which weather shocks are linked to a child health and how receipt of a social safety net might intervene to remedy this effect. Therefore we focus on environmental conditions existing during early stages of a child's life and ask whether it is possible to remedy these effects with investment made later in life in the form of HSNP transfers. Our result is based on a reduced form relationship between negative environmental condition (drought exposure), receipt of HSN transfers and how these factors interact to influence a child's health outcomes. Our a priori assumption is that exposure to drought (inadequate rainfall) leads to a reduction in

[32] We acknowledge that households may also receive transfers from other households or members living in far away places. These transfers can be in form of cash, non-cash and in-kind donations. In this way, these transfers help increase household income which can be used for consumption purposes. For instance, after drought which cause massive animal deaths, asset rich households tend to share part of their herds with poor counterparts. We analyse the effects of these transfers in chapter three.

location-specific crop output. This reduction in yields has two effects: it reduces the amount of food available for household consumption. It also means that there is no surplus output to sell for immediate income and income used to purchase more nutrition dense foods in case of exposure to shocks. Given that credit and insurance markets are non-existent in these rural areas, households are held up in nutrition-based poverty traps. We hypothesize that exposure to drought will negatively impact on the nutritional status of given household members and especially so for children, thereby resulting in poor health outcomes in general. Our findings confirm our hypothesis. We show that exposure to weather shocks during early years of a child's life reduces height for age and weight for age Z- scores by 0.01 and 0.11 standard deviation when drought is measured in cumulative terms and during in utero, respectively while controlling for other covariates. We find strong evidence of buffering effects of HSNP transfer on cumulative drought for HAZ scores. Specifically, for children residing in treated sub-locations, we show that receipt of HSNP transfer reduces the effect of cumulative drought exposure by about 6 percentage points compared to those residing in control sub-locations. These results are statistically significant at conventional level and does not seem to vary when we used different measure of participation. Under WAZ, we find positive coefficients but statistically insignificant result when drought is measured in cumulative terms. These findings depict the limited existance of buffering effect of social safety net transfer on WAZ scores.

2.6. Estimation strategy

To identify the impact of drought on child nutrition and how investment later in life could remedy these effects, we estimate an equation 1.3, below:

$$H_{ihj} = \alpha + \beta X_i + \delta_2 D_j + \delta_3 HSNP_{hj} + \delta_4 \left(HSNP_{hj} * D_j \right) + \varepsilon_{ih} \qquad (1.3)$$

Where; H_{ihj} represents health outcomes (height-for-age Z scores (HAZ) and weight for age Z scores (WAZ)) for ith child from household h in sub-location j in survey year 2012.[33] $HSNP_{hj}$ is a treatment indicator which equals one if a household h received HSNP transfer in sub-location j and zero otherwise; D_j is a drought exposure variable in a given sub-location j. We

[33] We only selected HAZ and WAZ scores as dependent variables because they are short term indicators of child health. Moreover, they can easily be observed given the short period nature of our datasets. Other measures of child health like Weight for Height Z-scores (a measure of wasting) are mostly evidenced in instances where there are datasets spanning more than 5 years.

follow the literature and use HAZ as an objective measure of long run chronic malnutrition for children (under 5 years) and WAZ to capture long- and short-term nutrition status of children (Beaton, Kelly, Kevany, Martorell, & Mason, 1990). In addition, D_j captures drought exposure, which equals one if SPEI is less than -1.5 or otherwise (McKee et al., 1993). $HSNP_{hj}$ is a dummy variable that captures whether a child lived in a treated community (we refer to these households as treated) and zero otherwise, while X_i captures the covariates likely to influence child health indicators. The relevant explanatory variables used in this study include: the logarithm of total household monthly per capita consumption expenditure (adjusted for regional price differences), ownership of female cattle, camels and goats, household size (using OECD modified scale[34]), age (in years) of a child, age (in years) of a child squared, gender of household head (dummy), Tropical Livestock Unit (TLU) Access to improved water source, Access to improved toilet and the interaction between age of child (in years) and drought variable.[35] Finally, ε_{ihj} is a zero mean error term. We cluster robust standard errors at the sub-location level and apply household weights (provided with the dataset) to control for sample attrition.[36]

We therefore run two specific models with each child health outcome: model one when H_{ihj}= WAZ and model 2 when H_{ihj}= HAZ scores, using ordinary least squares (OLS) regression. As a sensitivity analysis, we ran a regression restricting HAZ and WAZ scores to absolute values of six standard deviation. According to WHO (2011) recommendation, HAZ and WAZ scores outside this range are likely to be due to measurement error. This restriction affect 4.79 and

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[34] The Organization for Economic Co-operation and Development (OECD) modified scale assigns a value of one to household head, 0.5 to any other adult household member and 0.3 to every other child (Hagenaars, Klass de-Vos & Zaidi, 1994).

[35] We applied sine hyperbolic transformation every time we mention logarithm in this thesis (Bellemare & Wichman, 2020). The advantage of this method is that it preserves zero values (about 2 percent of our sample had zero values) that would have otherwise been recorded as missing in the case of the traditional natural logarithm.

[36] A household weight is the inverse probability of being selected by strata. For HSNP poor beneficiary households (i.e., group A and B, see Appendix 4.1), household weights were calculated as; $W_i = \frac{N_i}{n_i}$ where; n_i denotes the number of HSNP households interviewed in a given sub-location i while N_i captures the number of beneficiaries listed in the HSNP administrative data for a given sub-location i. For non-poor, non-beneficiary households (i.e., group C and D, see Appendix 4.1), household weights were calculated as; $W_i = \frac{1}{[\frac{a_{ijk}}{A_{ijk}} * \frac{1}{b_{ij}} * \frac{1}{C_{ij}}]}$ where; A_{ijk} is the total number of non-beneficiary households residing in k in the selected settlement j and sub-location i; a_{ijk} is the umber of households residing in k in settlement j and sub-location i that were interviewed; b_{ij} is the total number of segments in settlement j and sub-location i (with $b_{ij} = 1$). Finaly, C_{ij} captures total number of settlement of type j in sub-location i. These weights were provided in the dataset (see Merttens et al., 2013).

0.15 percent of children under HAZ and WAZ scores, respectively. Our coefficient of interest is δ_4 which informs whether receiving a HSNP transfer compensates for the effects of drought experienced around the time of birth.

In addition, we determine the probability for a particular child to face stunting, being underweight. We follow common evidence that associates malnutrition to changes in HAZ or WAZ around -2 standard deviation and use a binary indicator that determines whether a child is stunted or not (Beaton et al., 1990). To capture the effects of stunting and underweight separately, we ran specifications where stunting or underweight are considered as dependent variables. Since nominal values of HAZ are different from the ones for WAZ, we use the threshold ($HAZ = -2; WAZ = -2$) provided in the literature (Beaton et al., 1990; de Onis & Blössner, 2003; WHO/UNICEF, 2006) to determine dummies that capture the probability of either being stunted or underweight. Therefore, this indicates that a child is considered stunted when ($HAZ \leq -2$) and underweight when ($WAZ \leq -2$) and we analysed this probability using Probit model. As the Probit model is sensitive to misspecification in the presence of many zero observations (as in our dataset), we also estimated complementary log-log regression as a sensitivity test for the Probit model.

To allow for international comparison, child health (proxied by HAZ and WAZ scores) was calculated using World Health Organization (WHO) 2006 child growth standards (World Health Organization, 2018). We find that (Table 3) HSNP operated in moderately dry areas (SPEI =$-$0.85) of Kenya and among households with approximately 5 members eating from the same pot. Also, households are poor with tropical livestock unit of about 9, two units below the optimal level of 11 units.

2.7. Results and discussion

In this section, we begin our discussion by providing descriptive statistics of the main variables in this study. We then report findings of the mechanisms through which drought-related shocks impact child health and confirm that drought increases monthly household food, health and total consumption expenditure levels. Finally, we tested the fragile male hypothesis of inter-uterine development that assumes that male children’s health is more impacted by drought than their female counterparts.

2.7.1. Sample demographic characteristics

We first run a student t-test on important variables in our study (Table 3). One striking result is that (on average and in all districts: Turkana, Mandera, Marsabit and Wajir), the prevalence of malnutrition is exceedingly high across all child health indicators. The children in HSNP sample have poor HAZ and WAZ scores relative to well-nourished reference population. Specifically, there is high prevalence of stunting and wasting at 30.1 and 25.6 percent respectively among HSNP children, depicting the burden of malnutrition in the region. The high prevalence of malnutrition may be attributed to drought that is frequent in the area. For instance, in 2011 the region was hit by massive drought which prompted food price hikes. In addition, the region is prone to sporadic communal conflicts over grazing land and watering points. This results in displacements of households, which are associated with increasing cases of child malnutrition in the region. Finally, it is striking that there seems to be no significant difference in the child health indicators for WAZ scores. There are two possible explanations for this. First, WAZ scores are long term measures of child health and thus, they often require more time (about 5 years) to manifest themselves. Given the short term period that is under review (i.e., two years since baseline survey), we suspect this might explain the limited variation that has been observed between HSNP treated and control's households child health WAZ indicators. Therefore our finding could also be thought of as a short term impact evaluation. Second, and most importantly, the 2012 survey just proceeded one of the worst drought season experienced by the HSNP districts, and this has resulted in food price hikes. As a result, this has forced poor households to reduce nutritious diets by reducing a household's purchasing power which in turn affected child health. The limited amount of nutrient available at household level might also explain the limited variation in the child health WAZ. The ability of diet diversification (after transfer) to reduce nutrient deficiencies has also been argued by Dietrich & Schmerzeck, (2019).

We find that HSNP districts were on average, moderately dry: SPEI of -0.85 (Table 3). This is consistent with local environment in 2012 and this fits well with the aim of HSNP of reaching poor and vulnerable households in arid and semi-arid areas. Depending on the given year and month of birth, children were exposed to between 0 and 4 droughts from in-utero to age 5 (and including age 5). Finally, the distribution of birth month is fairly even throughout the year in both control and treated sub-locations (Figure S2.6, in Appendix 2.6).

Table 3: Descriptive statistics

Variables	Mean (Full sample)	Treated Households	Control Households
Child level variables			
Age of child (Months)	29.62 (0.39)	30.47 (0.54)**	28.73 (0.57)**
Weight-for-Age Z scores	-1.26 (0.04)	-1.26 (0.06)	-1.26 (0.05)
Underweight (% of sampled children)	28.40	28.95	27.92
Height-for-Age Z scores	-1.08 (0.07)	-0.98 (0.11)	-1.19 (0.09)
Stunted (% of sampled children)	30.24	27.03	33.53
Household level variables			
Household size (OECD scale)	4.89 (0.05)	4.95 (0.07)	4.83 (0.07)
Receipt of supplementary feeding (Dummy)	0.13 (0.01)	0.13 (0.01)	0.14 (0.01)
Tropical Livestock Unit (TLU)	9.20 (0.36)	8.93 (0.53)	9.48 (0.49)
Farm income (KES, annual)	4.98 (0.15)	4.83 (0.21)	5.13 (0.21)
Total consumption expenditure, KES, monthly	9.96 (0.01)	10.00 (0.02)***	9.90 (0.02)***
Food expenditure, KES, monthly	9.73 (0.01)	9.77 (0.015)***	9.70 (0.02)***
Health expenditure, KES, monthly	2.05 (0.06)	2.18 (0.08)**	1.92 (0.08)**
Access to improved toilet (Dummy)	0.16 (0.11)	0.22 (0.02)***	0.11 (0.01)***
Access to improved water source (Dummy)	0.19 (0.01)	0.22 (0.02)***	0.16 (0.01)***
Days household food insecure (Last 30 days)	14.44 (0.25)	14.85 (0.37)*	14.01 (0.34)*
Ownership of female goat (Numbers)	11.81 (0.40)	10.80 (0.51)**	12.84 (0.62)**
Ownership of female cattle (Numbers)	0.60 (0.04)	0.58 (0.07)	0.62 (0.07)
Ownership of female Camel (Numbers)	1.88 (0.10)	1.91 (0.14)	1.85 (0.14)
Community level variables			
SPEI during in utero period	-0.85 (0.03)	-0.82 (0.04)	-0.89 (0.04)
SPEI during land preparation and planting season	-0.29 (0.02)	-0.27 (0.02)	-0.30 (0.03)
SPEI during mid season	-0.28 (0.02)	-0.28 (0.03)	-0.28 (0.03)
SPEI during Harvesting season	-0.29 (0.02)	-0.27 (0.03)	-0.30 (0.03)
Drought in utero (Dummy, 1=Yes)	0.25 (0.43)	0.25 (0.43)	0.24 (0.43)
Cumulative drought (0-5 years)	1.26 (0.02)	1.28 (0.03)	1.23 (0.03)

Notes: Significance level; *, ** and *** are 1, 5 and 10 percent respectively; SPEI is the Standardized Precipitation Evapotranspiration Index; Distribution of cropping seasons are shown in Appendix 2.5, under Figure S2.5; Total consumption expenditure is the log of total monthly consumption expenditure including rent (nominal terms); food and health expenditure are log of total monthly food and health expenditure (nominal terms); KES is Kenya Shillings; Figures in parenthesis are standard errors; % is percentage; Treated Households are HSNP poor beneficiary households in treated sub-locations, N=677; Control Households are HSNP poor, non-beneficiary households in control sub-locations, N=659; Full sample, **N=1,336.**

Households had low on-farm income of about 12,759 Kenya Shillings (about USD 128) per annuum (Table 3). This low income might be due to over reliance on traditional livestock species with low milk production and prices in local markets, when they get sold. Also, HSNP households (i.e., both HSNP poor beneficiary and non-beneficiary households, See Figure 1) have low total monthly per capita expenditure (approximately USD 115) but large household sizes, averaging about 4.8 members. These results are similar to those of Bobonis (2009) who observed low levels of household expenditure among Mexico's PROGRESA recipients. We also find that households spend more of their income on food, averaging over 80 percent of the total monthly household expenditure per adult equivalent. This implies that HSNP households were income poor. This finding remains consistent with conventional stylized fact in the economic theory that argues that at low levels of income, households spend much of their income on food (Frazao et al, 2007).

Similarly, we find that both HSNP households (i.e., poor and non-poor beneficiaries) had limited access to improved toilet facilities (16 percent) and clean water sources (19 percent). The differences between treated and control households are statistically significant in this instance, implying that treated households had better access to these services than control households. This limited access to clean water sources might increase chances of families getting water borne related disease infections. As a result, nutrient absorption might be significantly impacted thereby worsening the health status of children. In terms of assets, HSNP households are asset poor with a low Tropical Livestock Unit (TLU) of about 9, far below the recommended minimum of between 11-15 TLU necessary to support recovery from a disaster. Most households own female goats and camels compared to cattle which can be considered as male assets. These female animals are important for child health in that they provide milk which is an important ingredient in growth and development process, especially at younger age.

Our results show that children were on average in the 2.5 years age group and live in households with approximately 4.8 members eating from the same cooking pot. We find that few households received supplementary feeding assistance excluding school feeding programs. This is surprising considering the fact that, in this region, the United Nations Children's Fund (UNICEF) had been implementing supplementary feeding programs targeting poor households. One reason for this could be that households were not willing to report their correct position for fear of being left out of the program.

2.7.2: Effect of drought on child health inputs

To test whether exposure to drought increases investment that parents make on child health inputs, we examined the effect of drought on household resources such as monthly food, non-food, health and total consumption expenditures and on farm incomes. Specifically, we regressed the cumulative drought (0-5 years) exposure variable on household resources and consumption share of household resources including child, household and community specific covariates. As a robustness check, we also undertook the same regression with drought measured during in-uteroine period only. Table 4 and in appendix 2.1.1 (Tables S1.0 and S1.1) below presents the result of these regressions. We provide additional tests for using our drought measures in Appendix 2.9 (Figures S2.91 and S2.9.2 and Table 2.9).

Table 4: Effect of drought on child health inputs

	Household comparison		Drought shocks	
	(1)	**(2)**	**(3)**	**(4)**
Variables	**HSNP poor beneficiary households**	**HSNP poor, non-beneficiary households**	**Drought (0-5 years)**	**Drought in-utero (Dummy)**
Panel A: Household resources (Kenya Shillings)				
Total expenditure	12,100.56***	10,923.59***	-0.06	-0.04
	(216.75)	(176.74)	(0.08)	(0.06)
Farm income	11,585.91**	13,964.98**	-0.20	-0.59
	(632.23)	(693.75)	(0.68)	(0.74)
Food expenditure	9,400.98***	8,761.33***	-0.06	-0.04
	(149.56)	(138.26)	(0.07)	(0.07)
Non-food expenditure	2,274.29***	1,815.15***	-0.05	-0.02
	(71.24)	(54.45)	(0.12)	(0.09)
Health expenditure	194.52**	148.06**	0.20	0.62***
	(13.18)	(14.36)	(0.36)	(0.22)
Panel B: Consumption expenditure and farm income shares (%)				
Food share	0.79***	0.82***	-0.32	-0.55
	(0.00)	(0.00)	(1.38)	(1.67)
Non-food share	0.18***	0.16***	-0.00	-0.00
	(0.00)	(0.00)	(0.01)	(0.01)
Health share	0.02**	0.01**	0.01	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
Farm income share	0.39	0.41	0.00	-0.05
	(0.02)	(0.02)	(0.05)	(0.06)

Notes: Dependent variables (columns 3 & 4, part A) are a log of total expenditure, farm income, food, non-food and health expenditures; In columns 3 & 4, part B, dependent variable are food, non-food and health shares of total expenditure; Robust standard errors (in parentheses) are clustered at the sub-location level; significance level *** p<0.01, ** p<0.05, * p<0.1; Each entry in columns 3 & 4 is from a separate regression; Total expenditure is the total monthly household consumption expenditure including rent in nominal terms; Farm income is the total income accruing to a household from activities related to the farm; Food, non-food and Health expenditure are the total monthly household food, non-food and health expenditure in nominal terms respectively; consumption share is a ratio of expenditure item (food, non-food or health) and total expenditure; Farm income share is ratio of total farm income to total household income; covariates include religion of a household, Tropical Livestock Unit, Access to improved water source, Access to improved toilet, Household size (OECD scale), Age (in years) of a child, Age (in years) of a child squared, gender of a child; Here, we report only coefficients on the interaction between drought exposure and HSNP under Column 3 and 4; **N=1,336.**

One key result (in Table S1.0, Appendix 2.1) is that the effects of drought exposure on household expenditure are positive under cumulative drought exposure conditions except for non-food expenditures. Specifically, we find that a unit increase in cumulative drought exposure, measured between 0-5 years, result in about 6 percent increase in monthly household total consumption expenditure (in nominal terms) for households residing in treated compared to those in control sub-locations, 24 months after the launch of HSNP in Kenya. Although this decrease in total monthly household consumption expenditure is not statistically significant at conventional levels (i.e., P<0.1), they depict the high impact a drought has on household consumption expenditure patterns. Here, our findings are in line with those of Asfaw, (2018) who found that a unit standard deviation increase in most recent rainfall shock increased a household's real per capita consumption expenditure by 3.26 Ethiopian Birr, a result which was significant at five percent level. Although not statistically different from zero, we find in addition that households residing in HSNP treated sub-locations and were exposed to cumulative drought witnessed a 6 percent reduction in food expenditure compared to those in control sub-locations (Table 4, Panel A, column 3). This decrease in consumption expenditure can be attributed to the high per unit cost of food during drought occasioned by disconnectedd local food markets from wholesale markets in cities like Nairobi, We observed for instance, higher amounts of food aid and supplementary feeding programs received by HSNP poor beneficiaries in treated households in the three months preceding the survey.[37] In addition, households reported receiving cash transfers, non-cash transfers and donations from religious organizations and development partners. We suspect that these decreases in expenditure might be attributed to asset fire sales- in this case livestock, a common form of savings often encountered in HSNP districts in Kenya. However, since we did not have livestock sales data during this precise period, we were not in a position to test this hypothesis.

We also estimated the effect of drought on household expenditure shares devoted to food, non-food and healthcare. As expected, we found that drought exposure increases expenditure shares that households devote to food but not to non-food items, farm income and healthcare. Specifically, we show that HSNP poor beneficiary households residing in treated sub-locations and were exposed to drought indeed increase their budget share for food by approximately

[37] The difference in the value of food aid and supplementary feeding programs between HSNP control and treated households are KES 60.113 (standard error of 623.793) and KES 255.470 (standard error of 169.328) respectively.

between 88 and 97 percent, respectively compared to those in control sub-locations. These findings are not statistically significant at conventional level (P<0.1), however they indicate the important share these items make in the basket of poor households.

Interestingly, however, we find that HSNP poor beneficiary households in treated sub-locations reduce their expenditure share allocation towards non-food items and healthcare compare to those in control sub-locations. Although these results are not statistically different from zero, they confirm our a priori hypothesis that assumes that households tend to decrease their investment towards their children's health during drought. Here, our results are consistent with Bobonis (Bobonis, 2009) who showed that PROGRESSA[38] recipient households reduced their expenditure allocation towards non-food items (clothing and other household goods) but increased expenditure on food items (meats, cereals and grains, fruits and vegetables). Our findings suggest that HSNP poor beneficiary households residing in treated sub-locations and were exposed to drought during in-utero periods observed a 5 percent decrease in farm income annually, although this result is not significant at economic level (i.e. P<0.1). Given the fact that a large proportion of households in rural areas depend on agriculture for survival and they also have limited access to formal credit, such large decreases in income present a special challenge to investment in child health. In summary, we show that drought exposure increases investments parents make on expenditure that touches on children's health and nutrition. Here, our result speaks again to those of Bobonis (Bobonis, 2009) who showed that exposure to drought (measured as an indicator variable for severe rainfall shock) reduced agricultural profits and earning potential of agricultural labourers.

According to past studies exposure to drought is associated with alteration of disease environment (Alderman et al., 2006; Asfaw & Davis, 2018; Maccini & Yang, 2009). This exposure to disease environment results in low absorption of micronutrient especially during early years of a child. To test this hypothesis, we estimate the effect of exposure to drought on healthcare expenditure and show that a unit increase in drought exposure during in utero periods for households residing in HSNP treated sub-locations result in approximately 62

[38] PROGRESA is Mexican government conditional cash transfer launched in 1997 covering 50,000 villages in 31 states. By end of year 2000, 2.6 million (representing 10% of all Mexican households) rural households were benefiting from the transfers on condition that they accept preventive medical care, children (0-5 years) and lactating women attend nutritional clinics and finally, pregnant women must attend clinics. These transfers were given to mothers only.

percent rise in health expenditure compared to those in control sub-locations. This result is statistically significant at conventional levels. A simillar result is confirmed by Maccini & Yang, (2009) who showed that exposure to high rainfall during birth year reduced chances of reporting poor or very poor health by 3.8 percent in Indonesia. We show that households that households residing in treated sub-locations and were exposed to drought during in utero periods reported a higher healthcare expenditure than those in control sub-locations and were exposed to cumulative droughts (i.e., 62 verses 20 percent) (Table 4).

As a robustness check, we undertake the same estimation using exposure to drought measured during in-utero period only. This is because past evidence suggests that shocks experienced during in-utero period have long lasting effects than those occurring at different periods of a child growth cycle (Almond & Currie, 2011). The idea here is that drought exposure results in food price hikes and this forces poor household to reduce consumption of nutritious diets which in turn affects child health. Our results (Table 4, column 4) show that households residing in HSNP treated sub-locations and were exposured to drought during this critical window observed about one percent increase in investment in child healthcare expenditure share on average compared to those in control households. However, when drought is measued in cumulative terms, we show that households that households residing in treated sub-locations reported a rise in health expenditure share (by about 1 percent) than those in control sub-locations (Table 4). Compared to the effect of cumulative drought (0-5 years), we find that exposure to drought during in-utero has a lower effect on child healthcare investment than exposure to cumulative drought.

We also find that households reduce their level of household expenditure for non-food items by larger margins when exposed to cumulative drought than when drought is measured during in utero periods. Specifically, HSNP pooor beneficiary households reduce their expenditure on non-food items by approximately one percent when drought is measured in cumulative terms compared to those in control sub-locations, and this result is not significant at economi levels. This reduction in expenditure is captured by mainly food consumption expenditure: higher expenditure shares on food when drought is measured in cumulative terms tthan during in utero periods.

2.7.3. Effect of early life drought on child health

We present the result of our main regressions (equation 1.1) on the effect of drought exposure on child health indicators (HAZ and WAZ scores) disaggregated by specific groups: i.e., 1) effect among children not receiving HSNP, 2) effects among children receiving HSNP, 3) effects of HSNP among children not exposed to drought and 4) effect of HSNP among children exposed to drought. We present these results in Table 5 and Table S2.2.1 (appendix 2.2). We find strong evidence that exposure to cumulative drought (0-5 years) reduces HAZ scores by about 1.95 standard deviations for children not exposed to drought and were residing in control sub-locations.[39] This result is statistically significant at one percent level depicting the high negative effects of drought on child health. At the same time, children who were exposed to drought and resided in HSNP treated households experienced worse WAZ scores than those in control households. Specifically, we show that exposure to drought measured during in utero periods lowers WAZ scores by a larger margin for children residing in treated than those in control sub-locations; i.e., 0.92 verses 0.50 standard deviations, respectively (Table S2.2.1, Panel B). These results are contrary to those reported in Table 3 that show that children in HSNP treated households as having slightly better health indicators (HAZ, WAZ scores) compared to those in control households. There are two potential interpretations that can be attributed to these unique findings. First, our result might be attributed to the small amount of HSNP transfer compared to program studied in other safety net programs. Second, our result is impacted by the presence of many (56 percent) Muslim households in our sample. Every year, Muslim households observe the holy Ramadan, a month during which pregnant women are exposed to fasting and evidence from previous studies has shown that this might influence the health outcomes of their children. For instance, Almond & Mazumder, (2011) and van Ewijk (2011) showed that exposure to fasting reduces child education outcome, birth weight and coronary heart problems and type two diabetes. Our result (in Table S2.2.3, in Appendix 2.2.) are consistent with these previous findings. We find that exposure to drought (either

[39] Importantly, standard deviation for HAZ and WAZ scores are 1.42 and 2.66 for the whole sample (N=1336). By treatment status, standard deviation are 2.79 and 2.53 for HAZ scores and 1.46 and 1.38 for WAZ scores in treated and control sub-locations, respectively. The calculation is as follows; 2.53*-0.77=-1.95 where 2.53 is a one standard deviation (for children in control sub-locations) and -0.77 is the coefficient on children exposed to drought but resides in control villages (Table S2.2.1).

measured in cumulative terms or during in utero) had a statistically significant and higher effects on child health indicators for muslim compared to Christian households. Moreover, we show that the effect of HSNP transfer is neutralized by the effect of Ramadan observance among Muslim families.

In a further regression, we analyse the effects of drought exposure on child health indicators and whether receiving HSNP transfer buffers these negative effects of drought exposure. We estimated these models separately for HAZ and WAZ scores and capture HSNP participation as an indicator variable which equals 1 when a child belongs to a treated household and 0 otherwise. As a robustness check, we also estimated the same models but using drought measured during the in-utero period (dummy) only. Table 5 presents the results of our regressions. Our variables of interests (in Tables 5 and 6) include drought exposure measures, program access and their interaction terms on HAZ and WAZ scores for each child. Our results provide suggestive evidence of a negative relationship between exposure to drought (measure during in utero period only, Table 6 or in cumulative terms, in Table 5) and child health indicators. The evidence is slightly stronger when drought variable (measured in cumulative terms or during in utero period) is regressed against HAZ scores than WAZ scores, respectively.

Table 5: Estimating the effect of drought on child health using OLS regression

Variables	**HAZ scores**			**WAZ scores**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Cumulative drought (0-5 years)	-0.50**	-0.45**	-0.56***	0.03	0.03	0.02
	(0.19)	(0.17)	(0.14)	(0.13)	(0.13)	(0.13)
HSNP (Dummy, 1=Treated)	-1.10*		-0.26	-0.08	-0.08	
	(0.55)		(0.50)	(0.25)	(0.25)	
HSNP exposure (Months)		-0.08*				-0.00
		(0.05)				(0.02)
HSNP exposure X Drought		0.06*				0.00
		(0.03)				(0.01)
HSNP X Cumulative drought	0.74*		0.38	0.02	0.02	
	(0.38)		(0.31)	(0.13)	(0.13)	
R-squared	**0.07**	**0.06**	**0.11**	**0.10**	**0.10**	**0.10**
Controls	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Observations	**1,336**	**1,336**	**1,272**	**1,334**	**1,336**	**1,336**

Notes: Dependent variables are HAZ and WAZ scores. Robust standard errors (in parentheses) are clustered at the sub-location level; level of significance *** p<0.01, ** p<0.05, * p<0.1; Cumulative drought is the number of droughts a child is exposed to from 0-5 years; HSNP exposure is self-reported number of months that a household has received transfer; In Column 3 and 4, we limit our dependent variables to absolute value of 6 standard deviations; all regressions include ownership of female cattle, camel and goats, access to improved toilet and water source, log of monthly household consumption expenditure, age (years) and age (years) squared and the interaction between age of child (in years) and drought variable but not reported here.

We find that exposure to drought during early life (0-5 years) had a negative and statistically significant effect on Height for Age Z (HAZ) scores. We found that a unit increase in cumulative drought exposure for children residing in HSNP treated households decreased HAZ scores by about 50 percentage points (or 0.01 standard deviation) compared to those residing in control sub-locations. This result is statistically significant at five percentage levels and does not change when participation in HSNP is measured differently or when we limit HAZ scores to absolute value of 6 standard deviations. Our results mirror those of Dasgupta, (2017) who found that exposure to cumulative drought reduced child HAZ scores in India by 0.98 standard deviation. Our findings contradict those of Bauer & Mburu, (2017) who observed a positive association between exposure to drought and child Mid Upper Arm Circumference (MUAC) score in Kenya. Similar to our result, they noted that a unit increase in drought exposure increase MUAC by 0.5 standard deviations.

We find strong evidence of the buffering effect of HSNP transfer on cumulative drought exposure for HAZ scores. Specifically, for children residing in treated sub-locations, we show that receipt of HSNP transfer reduces the effect of cumulative drught exposure by about 6 percentage points compared to those residing in control sub-locations. These results are statistically significant at conventional level and does not seem to vary when different measure of participation is applied. Under WAZ as a dependent variable, we find coefficients which are positive and not significant, depicting limited buffering effect of social safety net transfer on WAZ scores. Although our coefficients are not significant for the case of WAZ scores, they are in the spirit of Dasgupta, (2017) in the findings of non-significant buffering effect of the social safety net especially for HAZ scores. Although these result are not reported here for brevity but available upon request, we note that access to supplementary feeding programme increased HAZ scores by about 57 percentage points. We also observe that ownership of animals (female goat and camel) reduces HAZ scores by up to 5 percentage points, a result that is statistically significant at conventional levels. This relation reflects the fact that ownership of assets like female camel helps households access milk which, if consumed, can mitigate the effect of weather shock. Finally, we find a negative and statistically significant effect of household consumption on HAZ scores. Such a variable is significant and it has a negative sign suggesting that households enjoying higher level of consumption have lower HAZ scores.

As a sensitivety analysis, we limited our regression to children exposed to at least one drought during the 0-5 years of a child's life and those not exposed to any drought during their life. Our results show that exposure to at least one drought event worsens a child's HAZ score by about six percentage points (Table S2.2.2, in Appendix 2.2). These findings are statistically significant at one percentage points and does not seem to vary when we restrict our sample to children with absolute value of HAZ scores of 6 or exclude covariates in the analysis. Secondly, we find evidence that receipt of HSNP transfer buffers the negatve effect of drought (Table S2.2.2, Panel A) on HAZ scores but not for WAZ scores. These results are statistically significant at conventional levels ($P<0.1$).

As a robustness check, we estimate the above equation (1.3) using an alternative measure of drought exposure: an indicator variable which equals one if a child experienced drought during the in-utero period or otherwise. We present results in (Table 6 and in Appendix 2.3, Table S2.3.1) and confirm the negative effect of drought exposure on child health indicators: HAZ scores. The estimates on our measure of drought exposure are relatively low compared to those reported under cumulative drought exposure when participation is capture in terms of months of exposure. These results are contrary to the findings in Almond & Mazumder (2011) that highlight that droughts have long-term effects in- utero than those experienced during other stages of child development. Specifically, we observe a negative but not statistically significant effect of the interaction between exposure to drought and receipt of HSNP transfer on HAZ scores. The findings revealed that there is lack of evidence that a social safety net (HSNP transfer) aids poor households buffer the effects of weather shock. These findings are contrary to Dasgupta, (2017) findings which support the fact that safety net transfer can assist poor households to buffer the effect of weather shock in India.

Under WAZ scores, we find that the estimates on drought measured during in utero are slightly higher than those reported under cumulative drought. Here, our results speak to to those Almond & Mazumder (2011) findings that the effects of droughts experienced during in- utero period are feltfor several periods than those experienced during other stages of child's life. Specifically, we show that children residing in treated households experience worse WAZ scores by about 29 percentage points compared to those in control sub-locations. These results are statistically significant at one percent significance level. On whether participation in HSNP buffers the negative effects of drought, our findings show that receipt of HSNP does not cushion households against the negative effects of droughts experienced during in-utero period.

Instead, we observe that children residing in treated sublocation strongly experience worse WAZ scores by up to 55 percentage points compared to those in control sub-locations. These results are statistically significant at conventional levels and does not sem to vary even afwhen we apply different measure of treatment.

Table 6: Estimating the effect of drought on child health

	HAZ		WAZ	
Variables	**(1)**	**(2)**	**(1)**	**(2)**
Drought in utero (Dummy)	-0.11	-0.22	-0.26***	-0.29***
	(0.27)	(0.27)	(0.10)	(0.09)
HSNP (Dummy, 1=Treated)	0.01		0.12	
	(0.21)		(0.17)	
HSNP Exposure (Months)		0.00		0.02
		(0.02)		(0.01)
HSNP X Drought in utero	-0.71		-0.55***	
	(0.50)		(0.16)	
HSNP Exposure X Drought in utero		-0.05		-0.05***
		(0.05)		(0.02)
R-squared	**0.07**	**0.06**	**0.12**	**0.12**
Controls	**Yes**	**Yes**	**Yes**	**Yes**

Notes: Dependent variables are HAZ and WAZ scores; Robust standard errors (in parentheses) are clustered at sub-location level; level of significance *** p<0.01, ** p<0.05, * p<0.1; HSNP exposure is self-reported number of months that a household has received transfer (only for treated households); drought in utero- is a dummy of whether there was drought while a child was in utero; All regressions include ownership of female cattle, camel and goats, access to improved toilet and water source, log of monthly household consumption expenditure, age (years) and age (years) squared, and the interaction between age of a child (in years) and drought variable but not reported here; **N=1,336**.

Turning on to other covariates (we do not show these results here for brevity but are available form the authors upon request), we find that household consumption expenditure per month reduced HAZ scores by about 8 percentage points. These results are statistically significant at one percent significant levels. We further observe that aceess to female animals like goats significantly reduce short term child health indicators: HAZ scores by about 3 percentage points (or 0.11 standard deviations) for children residing in treated households compare to those in control sub-locations. Access to improved toilets, however, seems to increase a child WAZ score. For instance, children in households with access to improved toilets have higher WAZ scores than their counterparts without access to improved toilets. As such, we can conclude that WAZ scores are sensitive to environmental conditions that affect children's lives. We observed a simillar result concerning ownership of female animals on WAZ scores although they are not significant at conventional levels. In fact, ownership of household assets reduced HAZ scores. This can partly be explained by the fact that, in this region, having animals is viewed as a long term risk mitigation strategy, which means cattle are not often sold by households in case of drought. Households prefer to sell their cattle in situations where they have no other mitigation options.

2.7.4. Estimation of prevalence of stunting and underweight

We also analysed our results using stunting and underweight as outcome variables which equal to one if a child has a score which is less than or equal to -2 standard deviations. Using a dichotomous variable as a dependent variable means that Ordinary Least Squares (OLS) regression suffers from efficiency loss and specification bias (Greene, 2012). In this regard, we estimate a Probit model and report its marginal effects in Table 7 and in appendix 2.4, Table 2.4.1.

It must be highlighted that estimating a Probit model suffers from two limitations: the effect of a change in covariates depends on initial value of the outcome variable, and the effect of a change in covariates on the outcome variable is dependent on other covariates. Therefore, a Probit model may overestimate the effect of a change in covariate for individuals with probability close to one half of choosing any of the two alternatives. Therefore, to test the reliability of the Probit model, we also estimated a complimentary log-log model as suggested by Nagler (1994). A complimentary log-log model doesn't impose restrictions on marginal effects to be symmetric and its derivative is not necessarily maximized when $F(Xb) = 0.5$. We present results of both models for comparison in Table 7. Our emphasis is on the effect of drought and whether it is possible for affected children in HSNP treated households to recover from its effects if they receive investment later in life, proxied by receiving HSNP transfer. We discuss results related to the impacts of weather shock on child health and its interaction effects only, while controlling for other covariates that the literature has shown to effect child health.

Table 7: Effect of cumulative drought on child health using binary models

Variables	**Stunting**		**Underweight**	
	(1) Probit	**(2) Loglog**	**(1) Probit**	**(2) loglog**
Cumulative drought (0-5 years)	0.09**	0.09**	0.02	0.02
	(0.04)	(0.04)	(0.04)	(0.04)
HSNP (Dummy, 1= Treated)	0.04	0.05	0.08	0.09
	(0.05)	(0.06)	(0.09)	(0.09)
HSNP X Cumulated drought	-0.08	-0.07	-0.05	-0.05
	(0.05)	(0.05)	(0.06)	(0.06)

Controls	Yes	Yes	Yes	Yes

Notes: Dependent variables = Stunting and Underweight; Marginal effects are evaluated at sample means; Robust standard errors (in parentheses) are clustered at the sub-location level; level of significance-*** p<0.01, ** p<0.05, * p<0.1; Cumulative drought is measured as the total number of droughts a child is exposed from 0- 5 years; All regressions include ownership of female cattle, camel and goats, access to improved toilet and water source, log of monthly household consumption expenditure, age (years) and age (years) squared, and the interaction between age of a child (in years) and drought variable but not reported here; Probit and loglog are Probit and complementary log-log regressions, respectively; **N=1,336.**

We control for interactions effects in presence of nonlinear models – in this case the Probit model with dichotomous outcome variable (Ai & Norton, 2003; Norton, Wang, & Ai, 2004). Table 7 presents results for average stunting and underweight respectively with a cumulative measure of drought and in Table S2.4.1 (appendix 2.4) in with drought is measured as the number of months a household reported to have received HSNP transfer. One striking result is that cumulative drought exposure has a strong and positive effect on child health and especially so for stunting. We show that exposure to drought increases the probability of stunting and underweight. Specifically, we find that children residing in HSNP treated households and were exposed to drought were about 9 percentage points likely to be stunted compared to children residing in control households. These results are robust even when we limit our dependent variable to children with HAZ and WAZ scores between absolute values of 6 or when we estimate the regression with a different measure of treatment- number of months of exposure (Table S2.4.1). As expected, we observe a positive, although not significant, correlation between receiving HSNP transfer and child health indicators. On whether receiving HSNP transfer could mitigate the negative effects of drought, our result suggests otherwise.

We find a statistically insignificant and negative effects of the interaction between drought exposure and receiving HSNP transfers. We provide graphical representation of corrected interaction effects in presence of nonlinear models (appendix 2.1.0). Our result showed that stunting would have been biased downwards by almost 6 percent compared to uncorrected coefficients obtained using marginal effects. Although our results mirror those of Dasgupta, (2017), it is not clear whether she controlled for interaction effects in the presence of non-linear models in Table 11 and Table 16 (pages 796 and 799 respectively). If she failed to control for interaction effects, it is possible that her findings (in Table 11 and Table 16) are biased downwards by almost 5.9 percent.

When drought is measured as in cumulative terms but HSNP participation as self-reported months of exposure, we observe a similar and consistent negative effect of drought exposure on child health (Appendix 2.4, Table S2.4.1). Children residing in HSNP treated households and were exposed to drought during the earlier years of their life experienced worse HAZ scores by 8 percent compared to those residing in HSNP control households and this coefficient is statistically significant at five percent.

These children are not able to recover from such weather shocks when they receive cash transfer through HSNP transfer. We also observe a negative and statistically insignificant effect of receiving HSNP transfer on HAZ and WAZ scores. This can be attributed to two reasons; Firstly, HAZ scores measure long term effects and therefore contain information from past drought experienced in previous years (i.e., 2011 season). Secondly, the amount of HSNP transfer was a smaller amount which was not enough to cover households' nutrient needs given the high food prices in the region. This is evidenced when we compare HSNP coefficients with short term indicators like WAZ scores. Both short-term indicators are positive and depict that HSNP had a positive effect on child health. Yet when interacting HSNP with drought measures, we do not find any evidence that supports a possibility of a buffering effect from cash transfer. We observe a negative effect of transfer which was consistent with our priori assumption that receipt of a cash transfer would help smallholder households cushion the negative effects of malnutrition.

Turning to covariates, we observe that children residing in households that own female goats and camel observe improvement in HAZ scores compared to those not owning such animals. An additional result is that access to improved toilets had an opposite (i.e., negative) but statistically significant sign on the coefficient on child health indicators: HAZ and WAZ scores. This is surprising because having access to improved toilets is expected to reduce the prevalence of diseases, like cholera, which might hinder absorption of nutrition in order to provide better health conditions.

2.7.5. Fragile male hypothesis

Past evidence suggests that male children are more sensitive to early life nutritional shocks than female children (Almond & Currie, 2011; Almond & Mazumder, 2011; Eriksson, Kajantie, Osmond, Thornburg, & Barker, 2010). There are numerous channels through which exposure to early life shocks is expected to impact male children differently. Results from human biology show that women who are pregnant with male children are more likely to experience high miscarriages compared to women who carry female embryos (Eriksson et al., 2010). In the USA, Ralph Catalano, Bruckner, Anderson, & Gould, (2005) and Catalano, Bruckner, Marks, & Eskenazi, (2006) showed that, as a result of maternal stress arising from the 9/11 dust cloud, male children miscarriages were higher than those of females. Their findings reaffirm the idea that male children are more impacted by early life shocks than their female counterparts.

The second channel, through faster growth of male children before and during implantation (Pedersen, 1980), implies that male children require high levels of nutrient to support faster growth, due to the physical characteristics of their body systems. In the presence of shocks such as drought, the amount of available nutrients required for effective foetal growth is limited and this causes growth retardation, placental abnormalities and this may lead to death at a perinatal stage (Di Renzo, Rosati, Sarti, Cruciani, & Cutuli, 2007). Another equally important channel is through the long but minor diameter of placental surface inhibited by male children (Eriksson et al., 2010; Roland et al., 2013). This suggests that male children usually have a small placenta surface, meaning less reserve capacity for essential nutrient key in child growth. As a result, male children have higher dependency ratio on the maternal diet which, if limited, may result in poor life outcomes in adulthood.

To test the fragile male hypothesis, we estimated equation 1.3 above separately (with HAZ and WAZ as outcome variables) using gender disaggregation. We varied our measurement of drought by first using cumulative drought and second by using drought exposure during in-utero period only. We captured program participation as an indicator variable which equals 1 if a household is selected to receive HSNP transfer (treated) and 0 otherwise. Table 8 and Table S2.4.2 and Table S2.4.3 (in appendix 2.4) presents the result of our analysis.

Table 8: Weather shock effect size by gender

	HAZ		**WAZ**	
Variables	**(1) Male**	**(2) Female**	**(1) Male**	**(2) Female**
Panel A: Cumulative drought measure (0-5 years)				
Cumulative drought (0-5 years)	-0.51**	-0.57**	0.05	-0.01
	(0.23)	(0.24)	(0.27)	(0.14)
HSNP (Dummy, 1= Treated)	-0.95	-1.18**	0.17	-0.30
	(0.89)	(0.56)	(0.43)	(0.37)
HSNP X Cumulative drought	0.62	0.79	-0.09	0.10
	(0.59)	(0.46)	(0.27)	(0.23)
R-squared	**0.07**	**0.06**	**0.09**	**0.15**
Panel B: Drought measured during in-utero period (Dummy)				

Drought in utero (Dummy)	-0.31	-0.07	-0.22	-0.22
	(0.29)	(0.45)	(0.13)	(0.22)
HSNP (Dummy, 1= Treated)	0.09	-0.03	0.24	-0.01
	(0.27)	(0.23)	(0.22)	(0.15)
HSNP X Drought in-utero	-0.93*	-0.75	-0.66**	-0.46*
	(0.52)	(0.72)	(0.27)	(0.25)
R-squared	**0.08**	**0.06**	**0.12**	**0.17**
Observations	**689**	**647**	**689**	**647**
Control	**Yes**	**Yes**	**Yes**	**Yes**

Notes: Dependent variables are HAZ and WAZ scores; robust standard errors (in parentheses) are clustered at the sub-location level; level of significance *** p<0.01, ** p<0.05, * p<0.1; HSNP is dummy which equals one if household received treatment or otherwise; All regressions include ownership of cattle, camel and goats, access to improved toilets and water source, log of monthly household consumption expenditure per adult equivalence, age of a child (in years) and age of child (in years) squared, and the interaction between age of chld (in years) and drought variable but not reported here.

Our result fails to confirm the fragile male hypothesis for HAZ and WAZ under different drought scenarios. In all the models (of HAZ scores and drought measured in cumulative terms), we provide a qualified support that female children bear more burden than male counterparts, a result that is contrary to fragile male hypothesis. Specifically, we show that female children residing in HSNP treated sub-locations and were exposured to cumulative drought reported worse HAZ scores by approximately 57 percentage points compared to those in control sub-locations. The effect of cumulative drought exposure is higher for female than male counter parts: 57 verses 51 percentage points under HAZ scores. These results hold even under different model specification (see Table S2.42 and S2.4.3, Appendix 2.4). In general, we observe that when drought is measured in cumulative terms, the coefficients on female children seem to be much higher than those for male children. This implies that female children had a higher reduction in HAZ scores than male counterparts. It is interesting to note that under WAZ scores and drought is measured in cumulative terms, the coefficients on female children are positive and larger but the effect reverses when drought is measured as a dummy.

We find greater effect of drought on female children HAZ scores when drought is measured in cumulative terms than during in-utero period. Being exposed to drought during in-utero reduces both WAZ and HAZ scores of male children by between 22 and 31 percentage points compared to female children’s range of between 7 and 22 percentage points for HAZ and WAZ scores, respectively (Table 8). These results are not statistically significant at conventional levels. The fragile male hypothesis, however, seems not to hold for HAZ scores and especially when drought is measured in cumulative terms. However, under WAZ scores, we find that female children residing in HSNP treated households and were exposed to cumulative drought (0-5 years) reported a worse WAZ scores by almost one percentage points compared to those residing in HSNP control households. The effect is statistically insignificant at conventional levels. Although our result is not statistically significant at conventional levels, we find limited evidence of buffering effects of receiving HSNP on child WAZ scores.

As a robustness check, we analysed the same dataset but limited our cumulative drought exposure variable from in-utero to age 2 (between 0-2 years). Previous studies have shown that nutrition during a child's 1000 days (0-2 years) is important to a child's health (Horton & Steckel, 2013, 2014; Martorell et al., 2010). For those children who survived during this critical period, developed poor cognitive skills and educational performance, poor health conditions, which lead to lost productivity and low earnings in their later adult years. Our results (Table 9 and Table S2.4.4 (in appendix 2.4*)*) show in general that the coefficient on the interaction term (i.e., HSNP X Drought) for female children is reduced by 4 percentage points for HAZ scores and 16 percentage points for female children under WAZ scores (Tablle 9). However, in Table S2.4.4, we show that male children residing in HSNP treated sub-locations and were exposed to drought (measured in cumulative terms) observe a worse HAZ and WAZ scores by between 4 percentage points, respectively compared to children in control sub-locations (Appendix 2.4). However, receipt of HSNP transfer seems to only buffer the effects of drought for male children residing in HSNP treated sublocations compared to children in control sub-locations. However, this result is not statistically significant at conventional levels.

Table 9: Effect of weather shock by gender category

	HAZ		**WAZ**	
Variables	**(1) Male**	**(2) Female**	**(1) Male**	**(2) Female**
Cumulative drought (0-2 years)	-0.14	0.20	-0.04	0.05
	(0.24)	(0.21)	(0.16)	(0.11)
HSNP (Dummy, 1= Treated)	-0.30	-0.26	0.26	-0.04
	(0.53)	(0.27)	(0.29)	(0.22)
HSNP X Cumulative drought (0-2 years)	0.17	-0.04	-0.22	-0.16
	(0.44)	(0.36)	(0.17)	(0.15)
R-squared	**0.07**	**0.06**	**0.10**	**0.15**
Observations	**689**	**647**	**689**	**647**
Controls	**Yes**	**Yes**	**Yes**	**Yes**

Notes: Dependent variable- HAZ and WAZ scores; robust standard errors (in parentheses) are clustered at the sub-location level; level of significance *** p<0.01, ** p<0.05, * p<0.1; HSNP is dummy which equals one if household received treatment or otherwise; All regressions include ownership of female adult cattle, camel and goats, access to improved toilet, access to improved water source, log of monthly household consumption expenditure per adult equivalence, age (months) of child and age (months) of child squared, and the interaction between age of chld (in years) and drought variable but are not reported here for brevity.

As additional test, we limited analysis to households in which HAZ and WAZ scores are within an absolute value of 6 standard deviations (in Table S2.4.4, panel A). In Panel B (Table S2.4.4), we excluded all covarites shown under Table 9. Here, our result show that exposure to cumulative drought negatively impact HAZ scores for male than female children. Interestingly, we observe limited evidence of buffering effects for HAZ scores, although the results are not statistically significant at conventional levels (Table S2.4.4, appendix 2.4).

There are several implications that can be drawn from our foetal origin hypothesis results. Most important is that early life shock (especially drought) has a significant and strong negative effect on children's health. This means that more attention and support should be provided to pregnant women during this critical period. Given the resource limitation common in developing countries, it is important for governments to support initiatives that give more preference to poor households and safety net programs fits in this category.

Secondly, the effects for HAZ scores are larger when compared to WAZ scores under different drought measures. The third important finding is that both male and female children are vulnerable to early life shocks with the highest effect observed when drought is measured in cumulative terms. This means that nutritional intervention should target both male and female children. Such a policy might help improve the conditions for all children.

Our findings that show that both male and female children suffer burdens from weather shocks are consistent with broad literature findings on the impact of early life environment and the foetal origin hypothesis. For instance, Suzuki, Shinohara, Sato, Otawa, & Yamagata, (2016) showed that smoking during pregnancy (a form of early life shock) led to a reduction of male and female children birth weights. Dasgupta, (2017) showed that drought exposure had a negative and significant effect on Indian children's WAZ and HAZ scores. Similarly, Jedrychowski et al., (2009) showed that exposure to pollutants resulted in reduction of birth weight for male children. In USA, Currie & Schwandt, (2016) showed that dust arising from 9/11 terror attack had a negative effect on birth weight and especially on male children.

Intra-seasonal drought exposure and child health indicators

So far, we have assumed that the effect of drought experience during in utero period on child health indicators is homogenous throughtout the year. However, previous studies (see Farris, et al., 2021 and references there in) have shown that using annul measures attenuate the effects of weather shocks on child health. Specifically, using annual measures of weather shocks often masks critical diffeences in rainfall patterns that might be observed across different time periods, and this significantly impact crop yields. We address this challenge of using annual measures of weather shocks (in this case in utero drought exposure) by taking an intra-seasonal approach (Farris et al., 2021). This approach involves separating annul measure of weather shock into distinct cropping seasons.

As Kenya has two main seasons (i.e., major and minor) per year (Figure S2.5), we divided the two cropping seasons into three seasons: land and planting, mid and harvest seasons (see appendinx 2.5 part B for more discussion). We present result of our regression in Table S2.5.1 (Appendix 2.5). We find that shocks occurring during land preparation and planting and harvesting periods negatively impact child health indicators while those occurring during mid season increases child health indicators. These effects are not statistically different from zero (Table S2.5.1, Panel A). Moreover, we find that receipt of cash transfer by HSNP poor beneficiary households in treated sub-locations lowers the effects of mid-season shocks by approximately 160 percentage points compared to those in control sublocation. These effects of HSNP participation on drought are high under HAZ scores compared to WAZ scores. Another important result is that, children that were exposed to cumulative shock occuring during land preparation and planting and harvesting periods experienced worse child health indicators compared to those not exposed to cumulative shocks. Finally, we find (in Table S2.5.1. Panel A) that participating in HSNP transfer buffers the effects of drought experienced during mid-season period. These effects are statistically significant at conventional levels.

As a robustness check, we estimate the same regression but classified a sub-location as experiencing drought when SPEI<-0.84 and zero otherwise, akin to Agnew (2000) classification. We present the result in Table S2.5.1, panel B. We find that children who were exposed to drought during land preparation and planting and lived in HSNP treated sub-locations experienced more worse HAZ scores than those in control sub-locations. At the same time, we observe that the effects of drought on HAZ scores are higher than those of WAZ scores even under different definition of drought. Another important findings is that, children who were exposed to drought during mid season and resided in HSNP treated sub-locations reported poor HAZ and WAZ scores compared to those in control sub-locations (Table S2.5.1, appendix 2.5).

2.8. Conclusion

In this paper we explored the effects of cash transfer on child nutrition in the presence of drought using the Hunger Safety Net Program as an example. We find that on average 25 percent of the children (those below 5 years of age) were either stunted or underweight. We established that exposure to drought (measured either in cumulative terms or as a dummy during in utero period) increases health expenditures (in nominal terms) but reduces household total consumption, food, non-food consumption expenditures (in nominal terms) and annual farm income levels. Specifically, we show that HSNP poor beneficiary households in treated sub-locations increased their healthcare expenditure by 42 percent compared to those in control sub-locations. Our result on healthcare, non-food expendiitures and farm income is consistent with Bobonis, (2009) and Asfaw, (2018) findings in Mexico and Ethiopia respectively, that showed how drought exposure endangers the livelihood of poor people by increasing expenditure on basic goods.

Our findings show that cumulative drought exposure has much higher effect than drought exposure during the in-utero period. Our result from in utero period is contrary to the idea that interventions during early stages of life might have higher returns than those in later life. This means that interventions during this critical window (during in-utero) might not have higher returns than those undertaken in later periods of life as reported in previous studies. In addition, we provide evidence that confirms that exposure to drought worsens child HAZ and WAZ scores. Specifically, we show that HSNP poor beneficiary households in treated sub-locations and those that were exposed to cumulative drought reported lower (by about 50 percentage points) HAZ scores compared to those in control sub-locations. For WAZ scores, we show that HSNP poor beneficiary households in treated sub-locations reported worse WAZ scores by approximately 29 percentage points compared to those in control sub-location and when drought is measured in utero. Comparatively, we find that participation in HSNP (i.e., when HSNP is measured as a dummy variable) had stronger effect than when HSNP is measured as number of months of exposure. We find evidence that shows that receiving HSNP transfer buffers the negative effects of cumulative drought on child’s HAZ scores. Specifically, HSNP poor beneficiary households residing in treated sub-locations observed an improvement in HAZ scores by 74 percent compared to those in control sub-locations when drought is measured in cumulative terms. This result is statistically significant at conventional levels (i.e., $P<0.1$). For drought exposure during in-utero period, we find evidence that shows that there is possibility of remediation on WAZ scores for HSNP poor beneficiary households in treated compared to those in control sub-locations. Our results highlight the need to put more emphasis on the support delivered to poor households to assist them mitigate the deleterious effects associated with weather shocks.

Finally, we tested the fragile male hypothesis of intrauterine development which indicates that male children bear much burden associated with weather shock than female counterparts. Our findings are contrary to hypothesis for HAZ and WAZ scores. Specifically, we find that female children residing in HSNP poor households and were exposed to cumulative drought observed worse HAZ scores (by 57 percentage points) than those in control sub-locations. Compared to male counterparts, we showed that female children bear a higher burden of drought, and this effect is even higher when drought is measured in cumulative terms than during in utero periods and for HAZ scores. We further show that receipt of HSNP does not seem to help households mitigate the negative effects of drought measured in cumulative terms. The finding that the male foetus is a little more resilient to weather shocks than female foetus suggests the need to support pregnant mothers. How this should be done is an area for future research input. Finally, we analysed the effect of shock using Faris cropping season approach (Faris et al., 2021). Here, evidence suggest that weather shocks occurring during land preparation and planting and harvesting periods negatively impact child health indicators while those occurring during mid season increases child health indicators. Despite the fact that our results are not statistically different from zero, they suggests differences in impacts of drought on cropping seasons. Moreover, receipt of transfer by HSNP poor beneficiary households in treated sub-locations lowers the effects of mid-season shocks by approximately 160 percentage points compared to those in control sublocation. These effects of HSNP participation on drought are high under HAZ scores compared to WAZ scores. Another important result is that, participating in HSNP transfer buffer the effects of drought experienced during mid-season period.

This paper has several policy implications. Ensuring adoption of climate smart agricultural practices or economic diversification is key, given that drought exposure significantly reduces household farm income levels. This transition could be through adoption of drought tolerant cattle breeds or encouraging income diversification for poor households in order to reduce over reliance on agriculture for livelihood support. Other options might include growing drought tolerant crops, promoting capacity building that supports farmers planning and identifying niche opportunities. These would reduce risks and maximize long term opportunities and support additional market-linked initiatives (credit access, rural infrastructure development) that allow minimization of the effects of climate changes on poor households.

2.9.: Areas for further research

In this chapter, we have used cross-sectional dataset to unravel the effects of drought on child health and whether receipt of social safety net would help households recover from these negative effects. However, cross sectional datasets have one major weakness: in that it does not capture the time dimesion aspect common in panel datasets. We therefore recommend future studies to be undertaken using panel datasets. In this way, they can benefit from time dimension aspects in panel datasets. A second weakness of our analysis is that we have calculated drought variable over 12 months period to mimic local agricultural season in the HSNP districts. However, using 12 months period (akin to annual measure) is considered long and therefore not able to identify small changes in weather patterns that impact child health. Past evidence have shown that using annual measures may attenuate results from analysis. As such, we recomnd future studies to calculate SPEI using either three or six months period to allow for capturing of small variation in weather patterns- akin to seasonal approach.

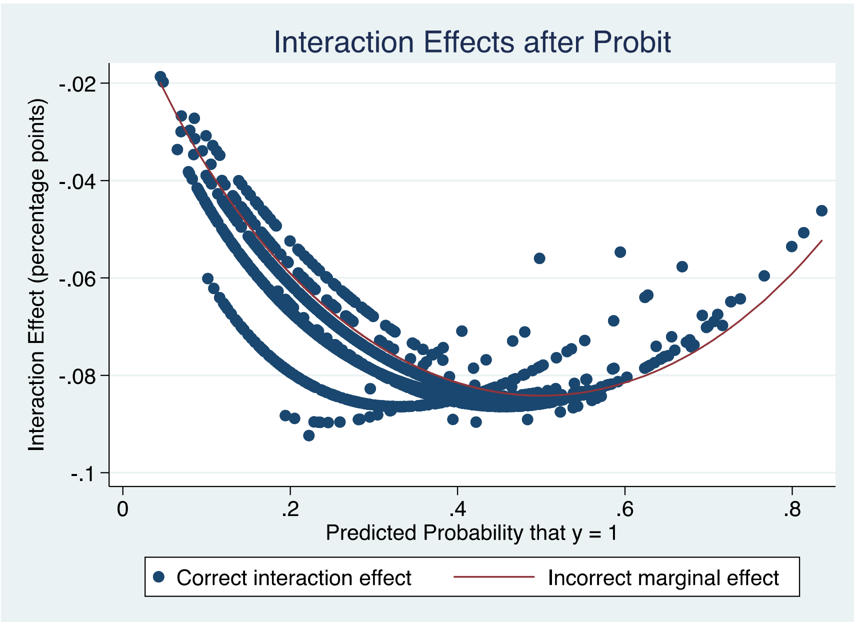
A third area for future work is to undertake same studies using datasets covering children of all parts of a country like Kenya. Using national datasets allow researchers to make general recommendations that might help governments to draft appropriate pollicies. Moreover, future work should analyse the effect of other natural calamities like floods which are more prevalent in low income countries. Finally, we used self reported measure of participation in the form of months of HSNP exposure. In a population where majority of people are illiterate like in rural Kenya, self reported measures are not likely to be accurate. Although we undertake several robustness check to reduce the effects of these misspecification, futuer studies should strive to make use more robust measures of program participation.

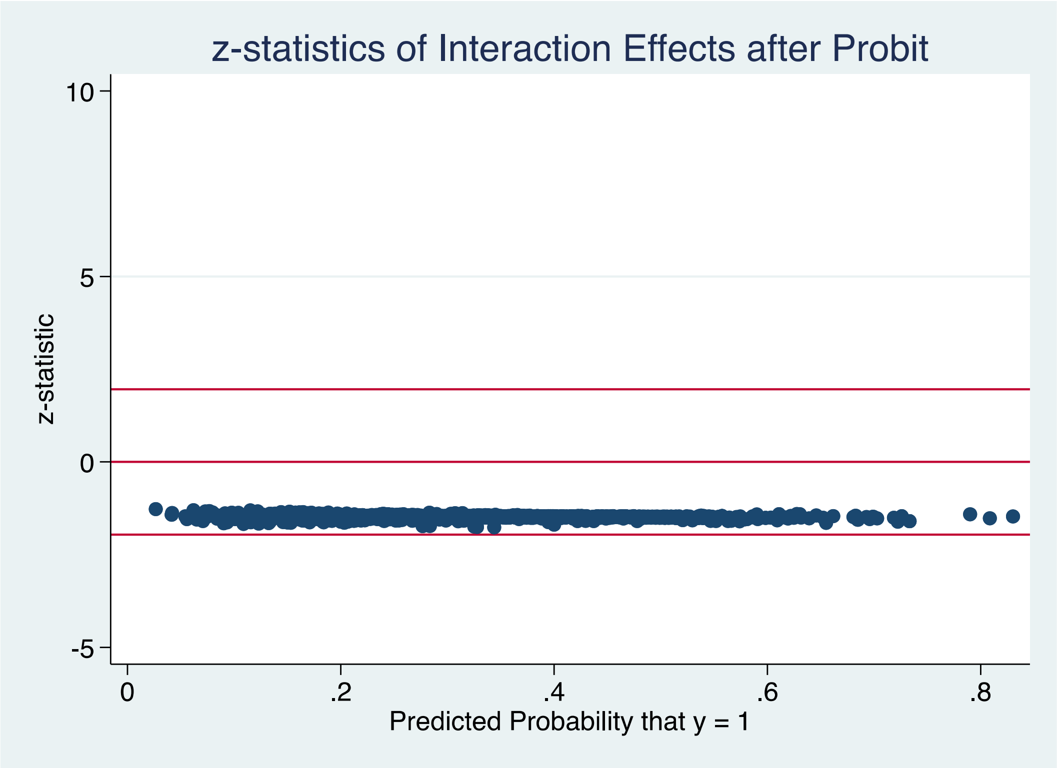
APPENDICES TO CHAPTER TWO

APPENDIX 2.1.0: INTERACTION EFFECTS IN PRESENCE OF NONLINEAR MODELS

We provide graphical representation of the interaction in our analysis of the impact of drought on child health indicators. Our interaction in the model result presented in Table 5 is a continuous variable (cumulative drought exposure between age 0-5 years) and an indication variable capturing receipt of HSNP transfer (whether a household live in treated sub-locations or otherwise.

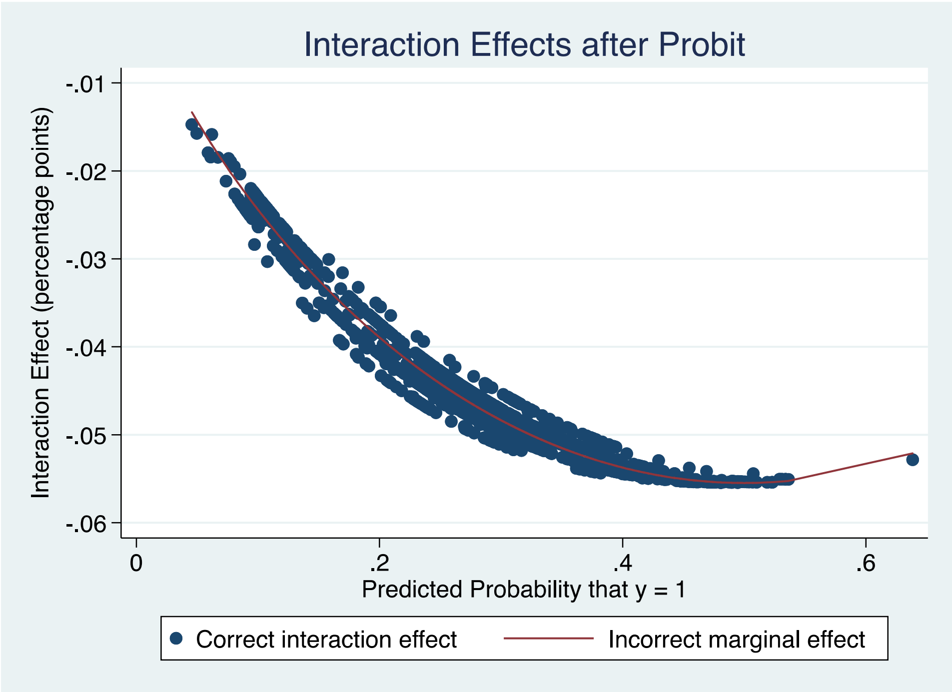
1A. HAZ dummy (1=HAZ<-2)

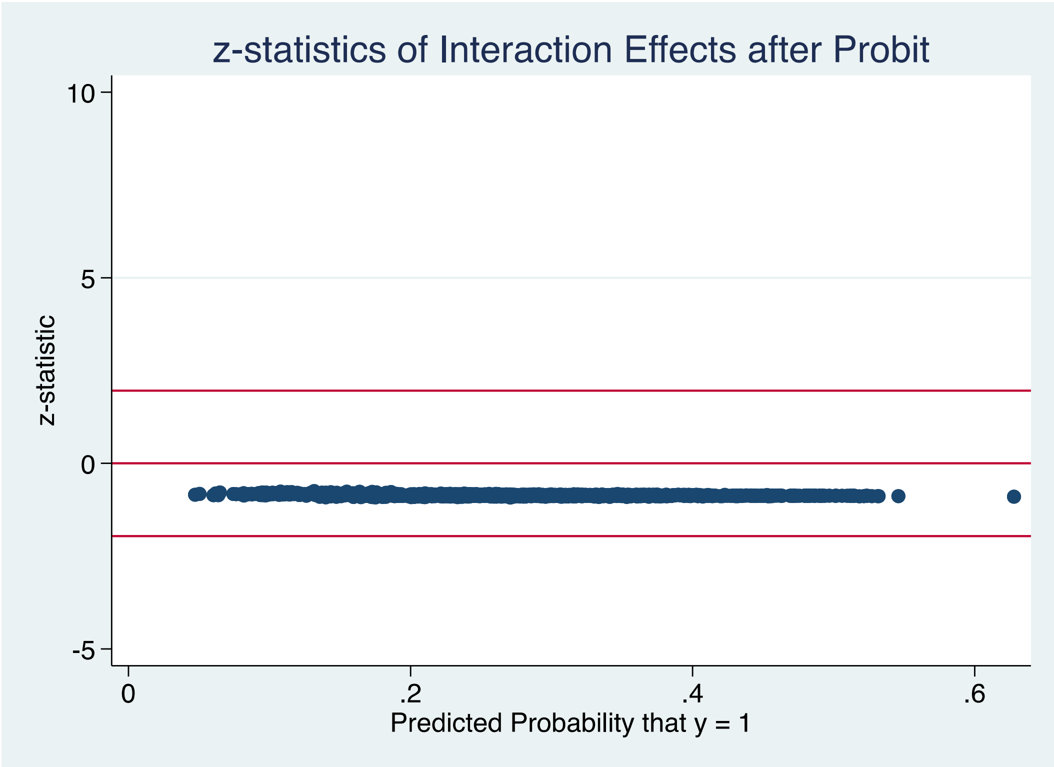




The correction result in about 5.9 percent increase in coefficient estimate to -0.08 with a standard deviation 0.02 compared to uncorrected marginal effect coefficients.

1B. WAZ dummy (1= WAZ<-2)





Here correcting for interaction effects does not significantly change the coefficients which stabilized at -0.05 and a standard deviation of 0.01. this coefficient is not significant.

APPENDIX 2.1.1: IMPACT OF DROUGHT ON CHILD HEALTH INDICATORS

Table S1.0: IMPACT OF DROUGHT EXPOSURE ON HOUSEHOLD EXPENDITURE

Variables	**Total (1)**	**Farm Income (2)**	**Food (3)**	**Non-Food (4)**	**Health (5)**
Panel A: Cumulative drought (0-5 years)					
Cumulative drought	0.05	0.16	0.06	-0.01	0.10
	(0.08)	(0.35)	(0.08)	(0.10)	(0.32)
HSNP	0.14	1.09	0.13	0.23	0.02
	(0.12)	(1.26)	(0.11)	(0.21)	(0.63)
HSNP X Cumulative drought	-0.06	-0.20	-0.06	-0.05	0.20
	(0.08)	(0.68)	(0.07)	(0.12)	(0.36)
R-squared	**0.47**	**0.14**	**0.34**	**0.60**	**0.10**
Panel B: Drought during in utero period					
Drought during in utero (dummy)	0.02	-0.18	0.03	-0.03	0.01
	(0.05)	(0.49)	(0.06)	(0.07)	(0.18)
HSNP	0.08	1.02	0.07	0.16	0.11
	(0.07)	(0.88)	(0.06)	(0.11)	(0.35)
HSNP X Drought during in utero	-0.04	-0.59	-0.04	-0.02	0.62***

	(0.06)	(0.74)	(0.07)	(0.09)	(0.22)
R-squared	**0.47**	**0.14**	**0.34**	**0.60**	**0.10**
Household control	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**

Notes: Dependent variables are logarithm of total expenditure, farm income, food, non-food and health expenditures; Robust standard errors (in parentheses) are clustered at the sub-location level; significance level *** p<0.01, ** p<0.05, * p<0.1; Total expenditure is the total monthly household consumption expenditure including rent in nominal terms; Farm income is the total income accruing to a household from activities related to the farm; Food, non-food and Health expenditure are the total monthly household food, non-food and health expenditure in nominal terms respectively; covariates include religion of a household, Tropical Livestock Unit, Access to improved water source, Access to improved toilet, Household size (OECD scale), Age (in years) of a child, Age (in years) of a child squared, gender of a child; **N=1,336.**

Table S1.1: IMPACT OF DROUGHT EXPOSURE ON EXPENDITURE SHARES

Variables	**Food (1)**	**Health (2)**	**Non-food (3)**	**Farm income (4)**
Panel A: Cumulative drought (0-5 years)				
Cumulative drought	0.88	-0.01	-0.00	-0.00
	(1.12)	(0.00)	(0.01)	(0.02)
HSNP	-0.57	-0.01	0.01	0.06
	(1.99)	(0.01)	(0.02)	(0.09)
HNP X Cumulative drought	-0.32	0.01	-0.00	0.00
	(1.38)	(0.00)	(0.01)	(0.05)
R-squared	**0.51**	**0.09**	**0.49**	**0.11**
Panel B: Drought in utero				
Drought during in utero	0.97	-0.00	-0.00	-0.01
	(1.42)	(0.00)	(0.01)	(0.04)
HSNP	-0.81	-0.00	0.01	0.08
	(1.17)	(0.00)	(0.01)	(0.06)
HNP X Drought in utero	-0.55	0.01***	-0.00	-0.05
	(1.67)	(0.00)	(0.01)	(0.06)
R-squared	**0.50**	**0.09**	**0.49**	**0.11**
Household control	**Yes**	**Yes**	**Yes**	**Yes**

Notes: Dependent variables are food, non-food and health shares of total expenditure; Robust standard errors (in parentheses) are clustered at the sub-location level; significance level *** p<0.01, ** p<0.05, * p<0.1; Total expenditure is the total monthly household consumption expenditure including rent in nominal terms; Farm income is the total income accruing to a household from activities related to the farm; Food, non-food and Health expenditure are the total monthly household food, non-food and health expenditure in nominal terms respectively; consumption share is a ratio of expenditure item (food, non-food or health) and total expenditure; Farm income share is ratio of total farm income to total household income; covariates include religion of a household, Tropical Livestock Unit, Access to improved water source, Access to improved toilet, Household size (OECD scale), Age (in years) of a child, Age (in years) of a child squared, gender of a child; **N=1,336.**

APPENDIX 2.2: IMPACT OF DROUGHT ON CHILD HEALTH INDICATORS, OLS REGRESSION

Table S2.2.1: Effect of drought on children health, by treatment status

Variables	HAZ scores		WAZ scores	
	Treated	**Control**	**Treated**	**Control**
	(1)	**(2)**	**(3)**	**(4)**
Panel A: Cumulative drought (0-5 years)				
Cumulative Drought exposure (Continous)	-0.11	-0.77***	-0.05	0.13
	(0.17)	(0.26)	(0.08)	(0.11)
Panel B: Drought during in-utero period				
Drought during in-utero period (Dummy)	-0.51	-0.49	-0.63***	-0.38***
	(0.42)	(0.32)	(0.11)	(0.09)
N	**677**	**659**	**677**	**659**
R-squared	**0.08**	**0.10**	**0.14**	**0.13**
Controls	**Yes**	**Yes**	**Yes**	**Yes**

Notes: Robust standard errors (in parentheses) are clustered at the sub-location level; significance level *** p<0.01, ** p<0.05, * p<0.1; Treated and Control are regressions from children in households residing in sub-locations selected to start receiving HSP transfer while control refer to regression on children from households residing in sub-locations not selected to start receiving HSNP transfer in the initial phase (i.e., control sub-locations); all regressions include age of child (in months), age of child (in months) squared, interaction between age of child (in months) and drought exposure variable, ownership (dummy) of female cattle, camel and goat, access to improved toilet (dummy), access to improved clean water (dummy), log of total household expenditure per month, access to supplementary feeding programme, the interaction between age (in months) of child and drought exposure levels.

Table S2.2.2: Effect of drought exposure on children health, by drought levels

Variables	HAZ scores		WAZ scores	
	(1)	**(2)**	**(3)**	**(4)**
Panel A: Children exposed to at least one drought				
Cumulative drought exposure (Continous)	-0.67*** (0.22)	-0.55*** (0.20)	0.17 (0.21)	0.17 (0.21)
HSNP (1=Treated)	-0.18* (0.47)	-0.55 (0.42)	0.11 (0.35)	0.11 (0.35)
HSNP X Cumulative drought	0.97*** (0.34)	0.54* (0.29)	-0.12 (0.21)	-0.11 (0.22)
N	**1,205**	**1,153**	**1,205**	**1,203**
R-squared	**0.10**	**0.02**	**0.10**	**0.10**
Controls	**Yes**	**Yes**	**Yes**	**Yes**
Panel B: Children not exposed to drought				
HSNP (1=Treated)	0.23	0.84	0.06	0.06
	(0.63)	(0.73)	(0.44)	(0.44)
N	**131**	**119**	**131**	**131**
R-squared	**0.18**	**0.23**	**0.37**	**0.13**
Controls	**Yes**	**Yes**	**Yes**	**Yes**

Notes: Robust standard errors (in parentheses) are clustered at the sub-location level; significance level ***

p<0.01, ** p<0.05, * p<0.1; In column 2 and 4, we restrict regression to child health indicators to absolute values of 6 standard deviations; all regressions include age of child (in months), age of child (in months) squared, interaction between age of child (in months) and drought exposure variable, ownership (dummy) of female cattle, camel and goat, access to improved toilet (dummy), access to improved clean water (dummy), log of total household expenditure per month, access to supplementary feeding programme, the interaction between age (in months) of child and drought exposure levels.

Table S2.2.3: Effect of drought exposure on children health, by religion of household head

Variables	**HAZ scores**		**WAZ scores**	
	Muslim	**Christian**	**Muslim**	**Christian**
Panel A: Cumulative drought (0-5 years)				
Cumulative drought (Continous)	-1.97***	-0.30	-0.49	-0.39
	(0.51)	(0.53)	(0.31)	(0.31)
HSNP (1=Treated)	-1.48***	-0.45	0.50	-0.12
	(0.33)	(0.57)	(0.45)	(0.39)
HSNP X Cumulative drought	0.88***	0.37	-0.14	-0.05
	(0.28)	(0.41)	(0.27)	(0.18)
N	**684**	**652**	**684**	**652**
R-squared	**0.17**	**0.03**	**0.13**	**0.08**
Controls	**Yes**	**Yes**	**Yes**	**Yes**
Panel B: Drought during in utero period				
Drought in utero (dummy)	-1.10***	0.31	-0.35*	-0.05
	(0.35)	(0.29)	(0.20)	(0.14)
HSNP (1=Treated)	-0.05	0.20	0.40*	0.04
	(0.20)	(0.45)	(0.22)	(0.25)
HSNP X Drought in utero	-1.60*	-0.64	-0.43*	-0.55***
	(0.93)	(0.43)	(0.24)	(0.20)
N	**684**	**652**	**684**	**652**
R-squared	**0.20**	**0.03**	**0.14**	**0.09**
Controls	**Yes**	**Yes**	**Yes**	**Yes**

Notes: Robust standard errors (in parentheses) are clustered at the sub-location level; significance level *** p<0.01, ** p<0.05, * p<0.1; In column 2 and 4, we restrict regression to child health indicators to absolute values of 6 standard deviations; all regressions include age of child (in months), age of child (in months) squared, interaction between age of child (in months) and drought exposure variable, ownership (dummy) of female cattle, camel and goat, access to improved toilet (dummy), access to improved clean water (dummy), log of total household expenditure per month, access to supplementary feeding programme and the interaction between age (in months) of child and drought exposure levels.

APPENDIX 2.3: EFFECT OF DROUGHT EXPOSURE ON CHILD HEALTH INDICATORS

Table S2.3.1: Estimating the effect of drought on child health using OLS

Variables	**HAZ scores**		**WAZ scores**	
	(1)	**(2)**	**(3)**	**(4)**
Panel A: HSNP dummy				
Cumulative drought (0-5 years)	-0.77***	-0.56***	-0.18	0.06

	(0.26)	(0.14)	(0.11)	(0.11)
HSNP (Dummy, 1=Treated)	-1.31**	-0.26	-0.14	0.23
	(0.61)	(0.50)	(0.33)	(0.26)
HSNP X Cumulative drought	0.82*	0.38	-0.03	-0.15
	(0.41)	(0.31)	(0.17)	(0.15)
R-squared	**0.02**	**0.11**	**0.01**	**0.13**
Panel B: HSNP exposure				
Cumulative drought (0-5 years)	-0.69**	-0.52***	-0.21*	0.04
	(0.26)	(0.14)	(0.11)	(0.11)
HSNP exposure (Months)	-0.10*	-0.01	-0.02	0.02
	(0.06)	(0.04)	(0.03)	(0.02)
HSNP exposure X Cumulative drought	0.06	0.03	0.00	-0.01
	(0.04)	(0.03)	(0.02)	(0.01)
R-squared	**0.02**	**0.11**	**0.01**	**0.13**
Controls	**No**	**Yes**	**No**	**Yes**
Observation	**1,336**	**1,272**	**1,336**	**1,272**

Notes: Dependent variables are HAZ and WAZ scores; In Column 2 and 4, we restrict HAZ and WAZ scores to absolute value of 6 standard deviations; robust standard errors (in parentheses) clustered at sub-location level; level of significance *** p<0.01, ** p<0.05, * p<0.1; HSNP is dummy which equals one if household received treatment or otherwise; All regressions in Column 2 and 4 include ownership of cattle, camel and goats, access to improved toilets and water source, log of monthly household consumption expenditure per adult equivalence, age in years, age in years squared, the interaction between age (in months) of child and drought exposure levels, but not reported here; All regressions in Column 1 and 3 exclude all covariates but cover all children irrespective of HAZ and WAZ score sizes.

Table S2.3.2: Estimating the effect of drought on child health using OLS regression

Variables	**HAZ**		**WAZ**	
	(1)	**(2)**	**(3)**	**(4)**
Panel A: HSNP dummy and drought in-utero				
Drought during in-utero (Dummy)	-0.21	-0.22	0.00	-0.34***
	(0.25)	(0.24)	(0.13)	(0.08)
HSNP (Dummy, 1=Treated)	-0.14	0.30	0.02	0.20
	(0.36)	(0.25)	(0.23)	(0.18)
HSNP X Drought in-utero	-0.57	-0.31	-0.73***	-0.49***
	(0.54)	(0.38)	(0.17)	(0.16)
R-squared	**0.01**	**0.10**	**0.03**	**0.15**
Panel B: HSNP exposure and drought in-utero				
Drought during in-utero (Dummy)	-0.31	-0.25	-0.03	-0.36***
	(0.27)	(0.24)	(0.13)	(0.08)
HSNP exposure (Months)	-0.02	0.03	0.00	0.02
	(0.03)	(0.02)	(0.02)	(0.02)
HSNP exposure X Drought in-utero	-0.04	-0.02	-0.06***	-0.04***
	(0.06)	(0.04)	(0.02)	(0.01)
R-squared	**0.01**	**0.10**	**0.03**	**0.15**
Controls	**No**	**Yes**	**No**	**Yes**
Observation	**1,336**	**1,272**	**1,336**	**1,334**

Notes: Dependent variables are HAZ and WAZ scores; In Column 2 and 4, we restrict HAZ and WAZ scores to absolute values of 6 standard deviations; robust standard errors (in parentheses) are clustered at sub-location level; level of significance *** p<0.01, ** p<0.05, * p<0.1; HSNP is dummy which equals one if household received treatment or otherwise; All regressions in Column 2 and 4 include ownership of cattle, camel and goats, access to improved toilets and water source, log of monthly household consumption expenditure per adult equivalence, age (in years) of a child, age (in years) of a child squared, the interaction between age (in months) of child and drought exposure levels, but not reported here. All regressions in Column 1 and 3 exclude all covariates but cover all children irrespective of HAZ and WAZ score sizes.

APPENDIX 2.4: EFFECT OF EXPOSURE DROUGHT AND HSNP (IN MONTHS) ON CHILD HEALTH INDICATORS USING PROBIT MODEL

Table S2.4.1: Weather shock effect size by gender

Variables	**Stunting**		**Underweight**	
	(1)	**(2)**	**(3)**	**(4)**
Cumulative drought (0-5 years)	0.08**	0.08***	0.01	0.00
	(0.04)	(0.04)	(0.04)	(0.04)
HSNP exposure (Number of months)	0.00	-0.00	0.00	-0.00
	(0.00)	(0.00)	(0.01)	(0.01)
HSNP exposure X Cumulated drought	-0.01	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Observation	**1,336**	**1,272**	**1,336**	**1,334**
Controls	**Yes**	**Yes**	**Yes**	**Yes**

Notes: Dependent variables = Stunting and Underweight; Robust standard errors (in parentheses) are clustered at sub-location level; level of significance-*** p<0.01, ** p<0.05, * p<0.1; Cumulative drought is measured as the total number of droughts a child is exposed from 0- 5 years; HSNP exposure is self-reported number of months that a household reported having received HSNP transfers; All regressions include ownership of cattle, camel and goats, access to improved toilets and water source, log of monthly household consumption expenditure per adult equivalence, age in years and age (in years) squared, the interaction between age (in months) of child and drought exposure level but not reported here; the coefficient on the Interaction term is the corrected for nonlinear model; In column 2 and 4, we report regression results for child health indicators with absolute value of 6 standard deviations.

Table S2.4.2: Weather shock effect size by gender

	HAZ		**WAZ**	
	(1)	**(2)**	**(1)**	**(2)**
Variables	**Male**	**Female**	**Male**	**Female**
Panel A: Cumulative drought measure (0-5 years)				
Cumulative drought (0-5 years)	-0.47***	-0.74***	0.05	-0.01
	(0.17)	(0.19)	(0.27)	(0.14)
HSNP (Dummy, 1= Treated)	-0.18	-0.22	0.17	-0.30
	(0.72)	(0.48)	(0.44)	(0.37)
HSNP X Cumulative drought (0-5 years)	0.30	0.36	-0.09	0.10
	(0.44)	(0.36)	(0.27)	(0.23)
R-squared	**0.11**	**0.10**	**0.09**	**0.15**
Controls	**Yes**	**Yes**	**Yes**	**Yes**
Observations	**663**	**609**	**688**	**646**
Panel B: Cumulative drought measure (0-5 years)				
Cumulative drought (0-5 years)	-0.66**	-0.87***	-0.12	-0.18
	(0.29)	(0.30)	(0.20)	(0.21)

HSNP (Dummy, 1= Treated)	-1.10	-1.49***	0.05	-0.28
	(0.92)	(0.52)	(0.38)	(0.50)
HSNP X Cumulative drought (0-5 years)	0.66	0.96**	-0.09	-0.02
	(0.59)	(0.43)	(0.25)	(0.27)
Observations	**689**	**647**	**689**	**647**
R-squared	**0.02**	**0.02**	**0.01**	**0.02**
Control	**No**	**No**	**No**	**No**

Notes: Dependent variables are HAZ and WAZ scores; In Panel A, HAZ and WAZ scores are limited to absolute values of 6 standard deviations while in Panel B, all children are included irrespective of HAZ and WAZ scores sizes; robust standard errors (in parentheses) are clustered at sub-location level; level of significance *** p<0.01, ** p<0.05, * p<0.1; HSNP is dummy which equals one if household received treatment or otherwise; All regressions in panel A include ownership of cattle, camel and goats, access to improved toilets and water source, log of monthly household consumption expenditure per adult equivalence, age (in years) of child, age (in years) of a child squared, the interaction between age (in months) of child and drought exposure levels but not reported here; All regressions in Panel B exclude all covariates but cover all children irrespective of HAZ and WAZ scores.

Table S2.4.3: Weather shock effect size by gender

	HAZ		**WAZ**	
Variables	**(1) Male**	**(2) Female**	**(1) Male**	**(2) Female**
Panel A: Drought in utero (Dummy)				
Drought in utero (Dummy)	-0.16	-0.25	-0.23*	-0.22
	(0.21)	(0.41)	(0.13)	(0.22)
HSNP (Dummy, 1= Treated)	0.39	0.24	0.23	-0.01
	(0.30)	(0.24)	(0.22)	(0.15)
HSNP X Drought in utero (Dummy)	-0.65	-0.14	-0.65**	-0.46*
	(0.42)	(0.46)	(0.27)	(0.25)
R-squared	**0.12**	**0.09**	**0.12**	**0.17**
Controls	**Yes**	**Yes**	**Yes**	**Yes**
Observations	**663**	**609**	**688**	**646**
Panel B: Drought in utero (Dummy)				
Drought in utero (Dummy)	-0.31	-0.04	0.05	0.01
	(0.36)	(0.33)	(0.18)	(0.26)
HSNP (Dummy, 1= Treated)	-0.09	-0.19	0.16	-0.12
	(0.39)	(0.35)	(0.26)	(0.23)
HSNP X Drought in utero (Dummy)	-0.71	-0.60	-0.85**	-0.68**
	(0.55)	(0.73)	(0.29)	(0.29)
Observations	**689**	**647**	**689**	**647**
R-squared	**0.02**	**0.01**	**0.03**	**0.04**
Control	**No**	**No**	**No**	**No**

Notes: Dependent variables are HAZ and WAZ scores; In Panel A, HAZ and WAZ scores are limited to absolute values of 6 standard deviations; robust standard errors (clustered at sub-location level) in parentheses; level of significance *** p<0.01, ** p<0.05, * p<0.1; HSNP is dummy which equals one if household received treatment or otherwise; All regressions in panel A include ownership of cattle, camel and goats, access to improved toilets and water source, log of monthly household consumption expenditure per adult equivalence, age (in years) of a child, age (in years) of a child squared, the interaction between age (in months) of child and drought exposure levels but not reported here; All regressions in panel B excludes all covariates but cover all children irrespective of HAZ and WAZ score sizes.

Table S2.4.4: Weather shock (0-2 years) effect size by gender

	HAZ		WAZ	
	(1)	**(2)**	**(1)**	**(2)**
Variables	**Male**	**Female**	**Male**	**Female**
Panel A: Cumulative drought (0-2 years)				
Cumulative drought (0-2 years)	-0.24	-0.03	-0.04	-0.03
	(0.16)	(0.18)	(0.13)	(0.10)
HSNP (Dummy, 1= Treated)	0.09	0.22	0.44*	0.09
	(0.43)	(0.25)	(0.26)	(0.22)
HSNP X Cumulative drought (0-2 years)	0.16	-0.06	-0.29*	-0.20
	(0.32)	(0.29)	(0.17)	(0.15)
R-squared	**0.11**	**0.09**	**0.12**	**0.20**
Controls	**Yes**	**Yes**	**Yes**	**Yes**
Observations	**663**	**609**	**663**	**609**
Panel B: Cumulative drought (0-2 years)				
Cumulative drought (0-2 years)	-0.40*	0.02	-0.04	0.09
	(0.22)	(0.40)	(0.21)	(0.15)
HSNP (Dummy, 1= Treated)	-0.47	-0.44*	0.25	-0.01
	(0.57)	(0.22)	(0.29)	(0.26)
HSNP X Cumulative drought (0-2 years)	0.24	0.04	-0.34	-0.36*
	(0.49)	(0.52)	(0.24)	(0.21)
Observations	**689**	**647**	**689**	**647**
R-squared	**0.01**	**0.01**	**0.01**	**0.02**
Control	**No**	**No**	**No**	**No**

Notes: Dependent variables are HAZ and WAZ scores; In Panel A, HAZ and WAZ scores are limited to absolute values of 6 standard deviations; robust standard errors (clustered at sub-location level) in parentheses; level of significance *** p<0.01, ** p<0.05, * p<0.1; HSNP is dummy which equals one if household received treatment or otherwise; All regressions in panel A include ownership of cattle, camel and goats, access to improved toilets and water source, log of monthly household consumption expenditure per adult equivalence, age (in years) of a child, age (in years) of a child squared, the interaction between age (in months) of child and drought exposure levels but not reported here; All regression in Panel B exclude all covariates but covers all children irrespective of HAZ and WAZ scores.

APPENDIX 2.5: INTRA-SEASONAL DROUGHT EXPOSURE AND CHILD HEALTH INDICATORS

Part A: Mechanism relating intra-seasonal drought exposure and child health indicators

Several studies (Maccini & Yang, 2016; Barker, 1998; Almond et al., 2017; Skoufias et al., 2011) have used annual measure of drought when estimating the effect of weather shock on child health (in this case HAZ and WAZ scores). However, using annual measure of drought obscar important differences in weather patterns across multiple time periods within a year (Farris, et al., 2021 and references there in). As a solution, we follow Farris cropping season approach which involves dividing annual season into distinct parts; i.e., land preparation and planting, mid season and harvest season. Such a detailed analysis requires information on the month of birth of a child (as shown in Appendic 2.6) and excellent knowledge of cropping pattern of the area of residence of achild, and especially so for households that rely on rainfed agriculture for livelihoods.

For rural households whose livelihood depends on agriculture like HSNP households, the effect of weather shock often operates through three chanels: labour requirement and stress borne by pregnant mothers, speed at which diseases spread and amount of crop harvested. For instance, good rains in a given season is a ssociated with excessive weed growth, and this calls for more labour. Given that it is mainly women who work in agricultural sector, this increase in labour demand is likely to be passed on to unborn child and thus impact child health indicators (Leight, Glewwe & Park, 2015). Another chanel is that linking disease exposure to changes in weather patterns. For instance, during drought there is problem of access to safe drinking water. As Maccini & Yang, (2009) showed, this is likely to worsen achievement of positive child health indicators.

A final channel is the one linking crop yield to changes in weather patterns across the lifecycle of crop. In most instance, most crops require less water during land prepatation and planting and harvest periods. However, there is high water requirement during flowering and or fruit formation. For instance, maize requires little rainfall during harvesting times to facilitate drying m than other periods (Barron et al., 2003). However, when there is excess rainfall, Steduto et al., 2012 noted that it leads to stress which in turn lower yield levels. This means that there is need to account for differences in season as two two seasons with same weather patterns can have different yield outomes. This means that yield obtained by households are dependent on the distribution of rain within a seson.

Part B: Distinguishing intra-seasonal drought exposure by cropping season

Kenya has two main agricultural seasons: long and short seasons. Long seasons are characterized by high rainfall and occurs between February and August every year. A short seasons are known for the sporadic rainfall patterns which are excellent for horticultural activites. It occurs between August and January every year. To account for the differences in intra-seasonal drought shocks, we split each agricultural season into three distinct cropping periods: land preparation and planting, mid and Harvest season. For the long cropping season, land preparation and planting season starts in February and ends in March; Mid-season from

April to May while harvest season occurs between June and July evey year. During short season, land preparation and planting occurs between August and September; mid-season between October and November while harvest season occur between December and January every year (see Figure S2.5).

Major season						Minor season					
Land preparation and Planting season		Mid-season		Harvest season		Land preparation and Planting season		Mid-season		Harvest season	
Season start		Growth stage		Season end		Season start		Growth stage		Season end	
Feb.	March	April	May	June	July	August	September	Oct.	Nov.	Dec.	Jan.

Figure S2.5: Cropping patterns in Kenya

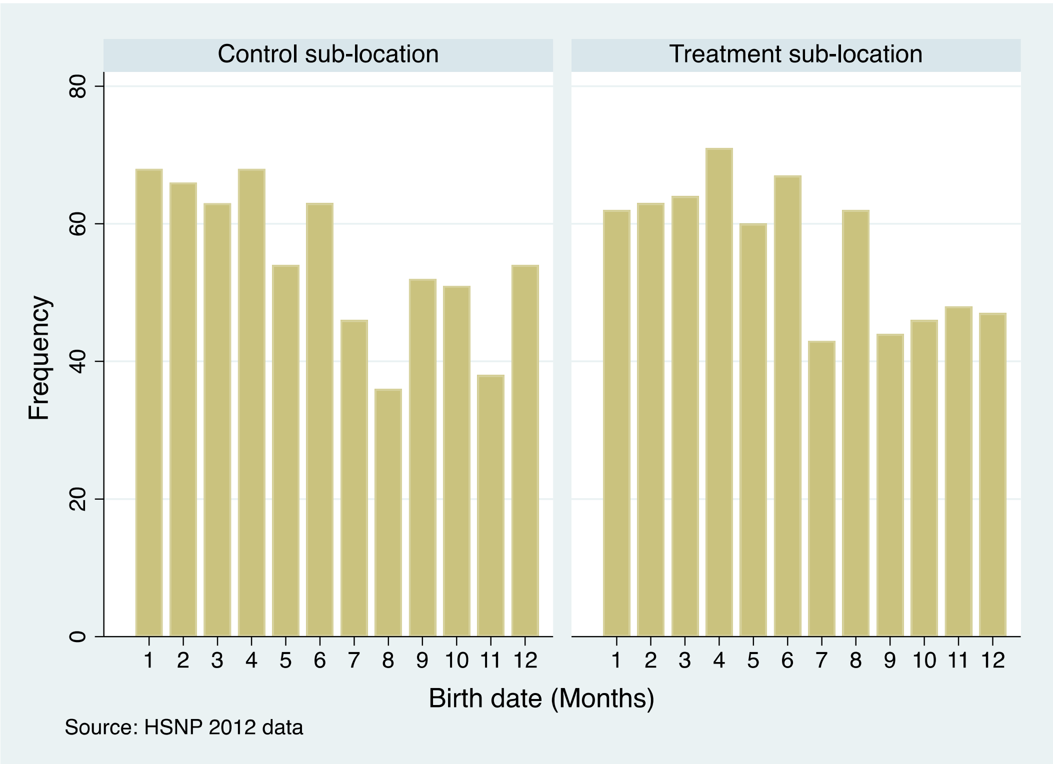
Table S2.5.1: Cropping season specific in utero drought exposure on child health indicators

Variables	HAZ scores		WAZ scores	
	(1)	(2)	(3)	(4)
Panel A: Drought during in-utero cropping season (=1 if SPEI<-1.50)				
HSNP (1=Treated)	0.32	0.02	0.11	0.11
	(0.25)	(0.21)	(0.17)	(0.17)
In utero land preparation and planting period drought shock	-0.54	-0.63	-0.41	-0.40
	(0.40)	(0.56)	(0.28)	(0.28)
In utero Mid-season drought shock	0.33	0.52	0.13	0.14
	(0.29)	(0.39)	(0.21)	(0.21)
In utero Harvest period drought shock	-0.94	-0.65	-0.52	-0.51
	(0.66)	(0.68)	(0.43)	(0.43)
HSNP X land preparation and planting period drought shock	-0.11	-0.67	-0.69	-0.69
	(0.52)	(0.96)	(0.43)	(0.43)
HSNP X Mid-season drought shock	-1.56**	-1.93***	-0.81**	-0.81**
	(0.59)	(0.68)	(0.35)	(0.35)
HSNP X Harvest period drought shock	0.59	0.30	-0.09	-0.09
	(0.72)	(0.77)	(0.38)	(0.38)
R-squared	**0.11**	**0.07**	**0.13**	**0.13**
Panel B: Drought during in-utero cropping season (=1 if SPEI<-0.84)				
HSNP (1=Treated)	0.55**	0.65**	0.32**	0.32**
	(0.22)	(0.30)	(0.15)	(0.14)
In utero land preparation and planting period drought shock	1.03**	0.58	0.30	0.31
	(0.46)	(0.40)	(0.19)	(0.19)
In utero Mid-season drought shock	0.60**	0.13	0.37	0.38*
	(0.28)	(0.21)	(0.23)	(0.23)
In utero harvesting period drought shock	0.34	-0.30	-0.17	-0.16
	(0.24)	(0.18)	(0.27)	(0.27)
HSNP X land preparation and planting period drought shock	-1.15*	-1.82**	-0.93**	-0.93**

	(0.60)	(0.77)	(0.36)	(0.36)
HSNP X Mid-season drought shock	-1.17***	-1.59***	-0.67**	-0.67**
	(0.30)	(0.36)	(0.33)	(0.33)
HSNP X Harvest period drought shock	-0.13	-0.63*	-0.30	-0.30
	(0.46)	(0.37)	(0.19)	(0.19)
N	**1,272**	**1,336**	**1,334**	**1,336**
R-squared	**0.11**	**0.08**	**0.12**	**0.12**
Controls	**Yes**	**Yes**	**Yes**	**Yes**

Notes: Robust standard errors (in parentheses) are clustered at sub-location level; Significance level *** p<0.01, ** p<0.05, * p<0.1; HSNP is a dummy which equals 1 if a child belongs to a household residing in sub-location selected to start receiving HSNP transfer and zero otherwise; land preparation and planting (planting), mid- and harvest season are dummy variables of SPEI experienced during in-utero period; In Column 2 and 4, we restrict HAZ and WAZ scores regression to absolute values of 6 standard deviations; All specifications control for age of child (in years), age (in years) of child squared, interaction between age of child (in months) and drought indicator, ownership (dummy) of female goat, cattle and camel, access to improved toilet, access to improved water source, log of total household expenditure per month, whether a household is receiving supplementary feeds, the interaction between age (in months) of child and drought exposure levels.

APPENDIX 2.6: DISTRIBUTION OF BIRTH DATE (IN MONTHS) OF HSNP CHILDREN



Notes: Birth date (in months) represent the following: 1 for January 2 for February 3 for March, … and 12 for December. Control sub-location represent children born to households residing in control sub-location while treatment sub-location represent children residing in sub-location s selected to start receiving HSNP transfer. These are self-reported values by mothers of children.

Figure S2.6: Birth date (in months) of HSNP children

APPENDIX 2.7: CONSTRUCTION OF DROUGHT INDICATOR USING STANDARDIZED PRECIPITATION EVAPOTRANSPIRATION INDEX (SPEI)

The data used in this study was obtained from University of Delaware Centre for Climatic Research. It is geocoded and covers 1976 to 2012 with a total of 56 meteorological stations distributed in the HSNP districts. To calculate SPEI, we followed four simple steps. In the first step, we decoded monthly precipitation and mean temperature datasets using QGIS software. We then aggregated locality specific monthly weather data using longitude and latitude. In the third step, we applied Thornthwaite method to calculate climate water balance (D_i) as the difference between precipitation (P) and reference evapotranspiration (ET_0) at 12 months' time scale. This value of D_i is aggregated over time considering total water balance over that period. We then used Log-logistic probability distribution to transform the original values to standardized units that are comparable in space and time at 12 months' time scale (see Beguería, Vicente-Serrano, Reig, & Latorre, 2014; Vicente-Serrano et al., 2012; Vicente-Serrano et al., 2011; Vicente Serrano, S.M., Beguiria, S. & Lopez-Moreno, 2010 for details). In the fourth step, we merge these SPEI values with HSNP child data using name of sub-location where a given household resides. We (Table 3a) provide a summary below of our SPEI values classification following McKee et al., (1993) but with limited extensions following Dinkelman (2006).

Table S2.7.1: Summary of drought classification scale for SPEI values

SPEI values	**Drought classification**		**Our classification**
	(McKee et al., 1993)	**(Agnew, 2000)**	
Greater than 0.00	No drought	No drought	No drought
Less than 0.00	Mild drought	No drought	
Less than -0.50	Moderate drought	No drought	
Less than -0.84	Moderate drought	Moderate drought	
Less than -1.00	Moderate drought	Severe drought	
Less than -1.28	severe drought	severe drought	
Less than -1.50	severe drought	Extreme drought	Drought
Less than -1.65	Extreme drought	Extreme drought	
Less than -2.00	Extreme drought	Extreme drought	

Source: Adapted from Agnew, (2000)

APPENDIX 2.8: SPATIAL DISTRIBUTION OF WEATHER STATIONS IN KENYA

In Figure S2.8 below, we provide spatial distribution of weather stations (in yellow dots) across Kenyan landscape with complete precipitation and temperature data covering 1976-2012 period.

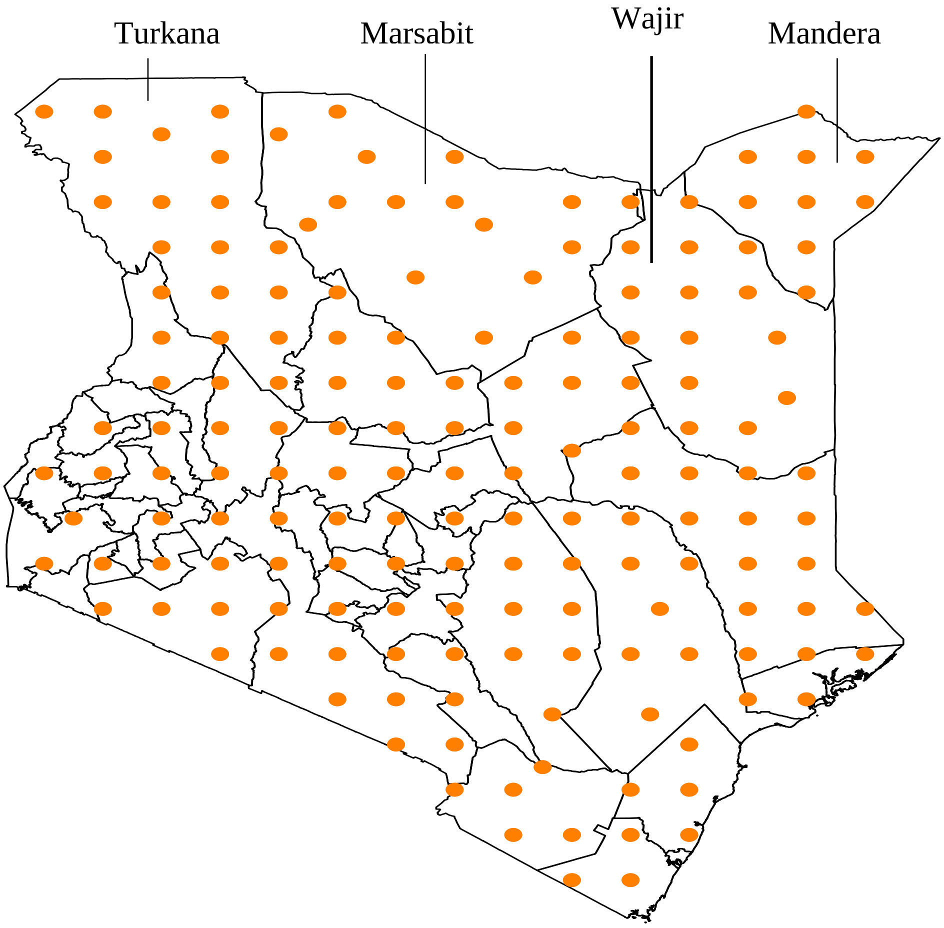


Figure S2.8: Spatial distribution of weather stations in Kenya

Our result (Figure S2.8) shows that there seems to be equitable distribution of weather stations across Kenya and HSNP districts. The four HSNP districts are located across the northern part of Kenya. There exist 56 stations of which we approximate 28 stations are covered by our sample. This variation allows us to instrument for farm income sources with confidence.

APPENDIX 2.9: MONTHLY FOOD CONSUMPTION EXPENDITURE AND SPEI, HSNP 2012 SAMPLE

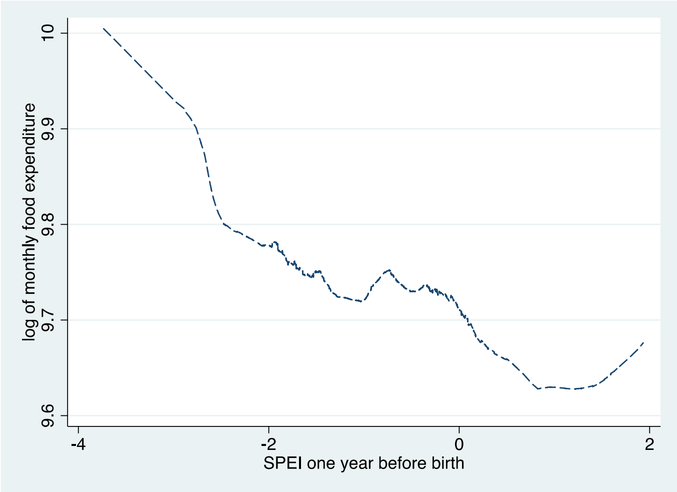


Figure S2.9.1: Association between SPEI before birth (continous variable) and the log of household monthly expenditure on food (in nominal terms)

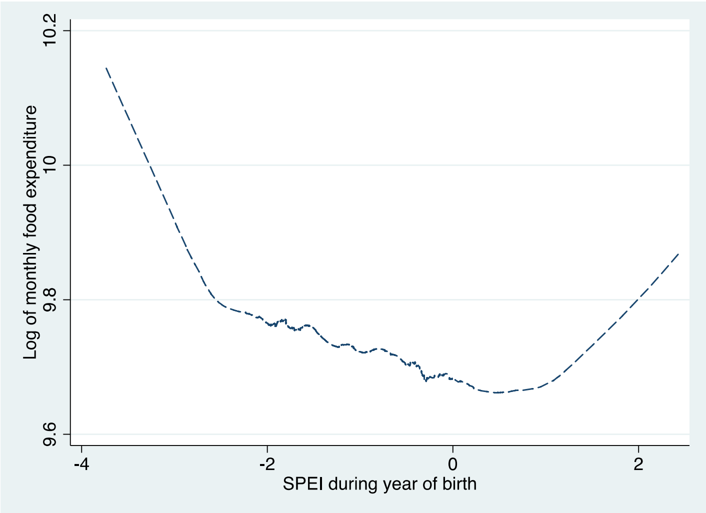


Figure S2.9.2: Association between SPEI during the year of birth (continous variable) and the log of household monthly expenditure on food (in nominal terms)

We show (in Figure S2.9.1 and S2.9.2) the negative correlation between exposure to drought during in utero and monthly household expenditure patterns. Specifically, during extreme drought conditions, households tend to allocate more expenditure towards food relatd items. We find a similar patterns when we estimate SPEI during year of birth and household monthly expenditure. These findings are a testament that our drought indicator dispalys correct pattern of expenditure by poor households: in that they increase expenditure during drought and a reverse is true.

Table S2.9: Effect of drought exposure during in utero period on community food prices

Variables	**Cereals** (1)	**Animal products** (2)	**Fruits and vegetables** (3)	**Food compliments** (4)	**Pulses and tubers** (5)
Drought in utero (1=Drought)	0.04*	-0.07**	-0.12**	0.13***	0.14***
	(0.02)	(0.03)	(0.06)	(0.03)	(0.05)
HSNP (1=Treated)	0.04	-0.17	-0.28*	0.11	0.03
	(0.04)	(0.11)	(0.15)	(0.11)	(0.12)
HSNP X Drought	-0.01	0.10*	0.07	0.05	-0.10
	(0.03)	(0.06)	(0.15)	(0.06)	(0.06)
R-squared	**0.06**	**0.10**	**0.11**	**0.15**	**0.03**
Household control	**No**	**No**	**No**	**No**	**No**

Notes: Robust standard errors in parentheses; significance level *** p<0.01, ** p<0.05, * p<0.1; cereals includes maize grain, maize flour (processed and posho), wheat flour, rice (loose and packed), loose and packed pasta; animal products includes eggs, fresh milk, powdered milk, sour milk, meat (goat and sheep), chicken and beef; fruits and vegetables includes Kales, cabages, tomatoes, tomato paste, onions and ripe bananas; food compliments includes tea leaves, coffee, Tobacco, Miraa, cooking oils, sagar, salt; pulses, tubers and roots includes dried beans; **N=1,335.**

Here, our intention is to show how drought experienced in agiven sub-location impact local food prices. We regresses the log of community food prices on drought experienced during in utero period (dummy), treatment status and the interaction on both. As expected, we observe a negative correlation between SPEI and community food prices for animal products, fruits and vegetables. At the same time, we observe a positive correlation between drought exposure and cereal prices, food compliments, pulses and tubers. Specifically, we show that children residing in treated sub-locations and were exposed to drought during in utero period witnessed higher prices of cereals by about 4 percentage points compared to those in control sub-locations. Comparatively, children residing in HSNP treated sub-locations paid higher prices for pulses and food compliments compared to those in control sub-locations. Given the fact that HSNP households are income poor and thus devote much of their income on cereals, these findings are testimony that exposure to drought over a long period of time might have a serious implication on human health. Our results mirror those of Dietrich & Schmerzeck, (2019) especially for food compliments, pulses, roots and tubers, animal products. The authors applied VCI to measure drought exposure.

CHAPTER 3: HOW ANTIPOVERTY PROGRAMS AFFECT INFORMAL TRANSFERS: THE ANALYSIS OF CROWDING OUT EFFECTS IN KENYA

3.1. Background and motivation

Transfer of wealth across generations is a complex network that involves neighbouring communities, friends, migrants and their families in countries of origin, the elderly and children. Amongst rural households in Africa, the pressure to share and mitigate risk is heavily driven by weather related shocks. These weather induced vulnerabilities are made worse by the non-functioning of credit and insurance markets, which in turn force households to rely on private (informal) transfers to cushion against shocks.[40] In undertaking these functions, private transfers act as ex-post emergency insurance schemes that facilitate a sharing of idiosyncratic shocks (Adams & Page, 2005; Cox, Hansen, & Jimenez, 2004; Townsend, 1994). Moreover, private transfers contribute to enhancing wealth redistribution amongst households with different socio-economic status. This is because, in the developing world, existing social norms often encourage endowment sharing between income rich households and the less fortunate or elderly members, especially after shocks (Lane, 1994; Merttens et al., 2013).

Although the exact value of private transfers is hard to quantify especially in developing countries where informal channels dominate most of the transactions that take place in the rural communities, in 2019, remittances (a major component of private transfer) totalled USD 554 billion globally (Ratha et al., 2020). In most African economies, remittances contribute up to 25 percent to the Gross Domestic Product (GDP) and reach more than one half of rural households (World Bank, 2005). In the recent past however (i.e. since 1980), social safety net

[40] Beyond assisting poor households to mitigate weather related risks, private transfers play other additional roles: labour pooling to allow ill farmers seek assistance from their neighbours to ensure their crops do not perish during harvesting seasons (Krishnan & Sciubba, 2009), child fostering that often takes place between close relatives in the developing world (Akresh, 2005).

programs[41] (especially cash transfers[42]) have been identified as optimal instruments that may help poor and vulnerable populations overcome multiple causes of poverty and rising inequalities. These programs are aimed at reducing the impact of shock induced poverty by transferring income and/or consumption to vulnerable households. In doing so, they compensate for market failures and provide poor households with the opportunity to diversify their income sources. In recent years, their mandates have expanded into human capital development as well as protection against social exclusion and marginalization (Devereux & Sabates-Wheeler, 2008). Although heterogeneity in implementation exists, most social programs are modelled around Mexico's PROGRESA[43] (now Oportunidades), launched in 1997. Thereafter, countries followed and set up their own versions of safety net programs before they either faded away or discontinued altogether.

In most instances however, these public transfers are implemented either in parallel with or are overlaid on the pre-existing private transfer arrangements (i.e., cash remittances, non-cash natures and in-kind donations). When public and private transfers provide similar social benefits, an overlap may occur and this has the potential to cause crowding out effects. It is estimated that, as a result of public social transfers expansion, between 20 to 91 percent of private transfers are likely to be displaced in developing countries (Haque, 2001). Despite this revelation, the economic theory still remains ambiguous in predicting the direction of transfer derivative[44] (Gibson et al., 2011). Some empirical studies have analysed the sign and magnitude of crowding out effects but findings are often mixed as they depend on whether the

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[41] These are non-contributory cash payments provided by governments in collaboration with other development partners (DFID, World Bank, IDRC, etc..).

[42] Currently, cash transfers are implemented in 136 countries worldwide, benefiting 1.9 billion people in Latin America, Africa and even in a developed country like USA (Honorati, Gentilini, & Yemtsov, 2015; World Bank, 2018).

[43] PROGRESA stands for Program of Health, Nutrition and Education and provides coverage to five million poor families in Mexico

[44] A transfer derivative measures the way private transfer receipt changes as a result of increase in household resources. The cause of ambiguity in economic theory prediction is caused by the motive of transfer under review. For instance, if the motive is altruism, then donors care about the welfare of recipients and thus any transferred amount is a function of the donor's and recipient's incomes (Barro, 1974; Becker, 1974). But when transfer is exchange motived, private transferred amounts are considered payments against services provided by the recipient to the donor (Bernheim et al., 1985; Cox, 1987; Foster & Rosenzweig, 2001). Finally, when the transfers motive is for mutual insurance, households join mutual agreements and transfer of transitory income helps smooth consumption (Townsend, 1994).

studies were conducted in a developing or developed country (Altonji, Hayashi, & Kotlikoff, 1997). Studies conducted using data from targeted developing countries like the Philippines, Mexico, Tonga and Vietnam often yield different results when it comes to identifying transfer derivates. For instance, Cox et al., (2004) and La and Xu, (2017) confirmed strong crowding out effects in studies carried out in Peru and Vietnam respectively, while Kazianga, (2006) observed weak substitution effects in Burkina Faso. There are also disagreements on the magnitude of transfer derivatives. In this, Brown and Jimenez, (2011) and La and Xu, (2017) found strong transfer derivative in Tonga and Vietnam respectively. Gibson et al., (2011) found weak transfer derivatives in Indonesia, Papua New Guinea, Vietnam and China while Cox et al., (2004) found a mix of both strong and weak transfer derivatives ranging from -0.06 to -1.06 in the Philippines. Additionally, a study (Nikolov & Bonci, 2020) comparing crowding out effects of various types of social transfers in the developing countries has found no ostensible pattern of variation of the effect size magnitude by country income classification. These mixed findings constrain precise estimation of welfare effects of substitution and call for further tailored and context-based studies to better understand the underlying conditions that support these divergent results, especially in a developing country's context where such effects are expected to be higher.

This paper revisits the crowding out effects literature by asking whether participating in a social safety net program[45] (a form of public social program) impacts private transfers received by poor households in rural areas of Kenya. We mean by private transfers, non-cash, cash remittances and in-kind donations made by friends or members of an extended family to their relatives. A clear answer to this question is important for several reasons. First, if crowding out effects exist, it implies mistargeting of limited public program resources in the sense that program benefits are accruing to households who shouldn't have been made beneficiaries, and

[45] The literature often identifies three types of social transfers (social assistance programs, social security and pension programs and other insurance types such as health and unemployment insurances). For instance, Nikolov & Bonci, (2020) provide a review of the various types of social transfers and investigate the extent to which their implementations might crowd out private transfers. In this paper we decided to focus on a social assistance programs (in the form of HSNP transfer) because this is the widely implemented type of public transfers targeting pastoralist communities in Kenya. A good understanding of the HSNP provides a clear guideline on whether the government must support its up taking to other poor and vulnerable communities in the country.

this creates spill-overs. These not really vulnerable households either receive both public and private transfers simultaneously or public transfer only but are not needy, signifying some element of inefficiencies.

The optimal allocation rule would favour public funding being directed towards poor households who need them the most, leaving other households who could more easily obtain private financial supports from their kinship ties and extended family networks. But if this is not achieved, the created spill-overs if large enough, may neutralize the benefits of participating in public transfers thereby posing a serious challenge to poor households who rely on government funding for their survival. Second, the presence of crowding out weakens income distribution effect of a social safety net and this may create deadweight losses, given the huge government administrative costs engaged during the public transfers (Cai, Giles, and Meng, 2006). Finally, information about crowding out effects reveals household's risk sharing behaviours, whose understanding can be of great importance especially during episodes of shocks.

Our analysis benefits from a unique randomized controlled trial panel dataset (Hunger Safety Net Programme, thereafter HSNP) collected in Turkana, Wajir, Marsabit and Mandera districts, in Kenya. HSNP is an unconditional cash transfer program aimed at improving household welfare in rural areas of Kenya. In these HSNP districts, about 70 percent of households are considered asset poor[46] and practise pastoralism. The rural nature of these districts offers an excellent ground for testing crowding out effects as the majority of the households rely on rain fed agriculture for livelihood support. Therefore, variability in weather patterns puts pressure on these households' income sources. Moreover, very few households

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[46] Asset poverty occurs when the number of assets a household has are below a set critical threshold which cannot allow them to maintain the least accepted living standards when exposed to shock (Brandolini, Magri, & Smeeding, 2010; Carter & Barrett, 2006). As that, it can be viewed as a vulnerability measure and not poverty per se (World Bank, 2001). Our asset based poverty measure is tied to the number of livestock (cattle, goat, sheep, donkey/Ass/Mule, camel) owned by a given household. We follow the literature and assign a value of one for every cattle owned: 0.1 for Donkey/Ass/Mule, 0.1 for Sheep or Goat 0.01 for Poultry and 1.4 for Camel. We summed these values to create a composite index called the Tropical Livestock Unit (TLU). Following classification a household with below 15 TLU (or herd size below 15 cattle) will converge to single head of cattle or fall into poverty when exposed to shock (Lybbert et al., 2004).

have access to credit[47] and poverty rates are exceedingly high[48]. These situations of vulnerability make households dependent on private transfers in presence of weather shocks to smooth consumption.

In these HSNP districts, there is a rich history of livestock sharing amongst households which is backed by cultural and religious norms (Lane, 1994; Merttens et al., 2013). These sharing arrangements allow poor households to expand the size of their livestock holdings and mitigate against sudden weather induced vulnerabilities. The benefit of using the HSNP dataset is that it contains detailed household level information on the amount of private transfers received, disaggregated by types (either as cash or non-cash transfers), household head characteristics, asset holdings, household income disaggregated into either farm and off-farm incomes. The fine disaggregation allows for the analysis of private transfer received by types, a feature that has been missing in most studies present in the current literature.

Using a regression specification, we find evidence that participating in HSNP reduces a household's likelihood of receiving positive private transfers by about 6 percentage points (ppt) and amounts received by up to 56 percent compared to baseline mean. At a sub-locational level, participating in HSNP reduces the likelihood of receiving private transfers by about 2 ppt and value of transfer received by Kenya Shillings (KES) 1,008 which is equivalent to 10 USD. Specifically, we confirm evidence of crowding out effects for non-cash transfer but not for cash transfer received. Our estimate of per Kenya shilling crowding out effects, range between 0.73 and 0.81 for non-cash transfers received under household and sub-location level fixed effects respectively, which is consistent with previous studies (Altonji et al., 1997).[49] We also show that receipt of public transfers significantly increases the probability of a household participating in the labour market, although this result is not statistically different from zero.

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[47] Specifically, In 2010 and 2011, 12.9 and 11.9 percent of households reported having received credit from formal financial institutions, respectively.

[48] In the HSNP districts, over 80 percent of households are classified as income poor (Merttens et al., 2013).

[49] Village level effects are those impacts that accrue to all households in a given village irrespective of whether they were selected or otherwise to receive HSNP transfers. Therefore, it cover those impacts accruing to HSNP and non- HSNP households (i.e., poor beneficiary and non-beneficiary, non-poor, non-beneficiary households, see Figure 2). Household level effects, on the other hand, refers to those effects acruing to households selected to participate in HSNP programme (i.e., poor beneficiary verses non-poor beneficiary households) only (see Figure 2 for details).

Here, our result is contrary to earlier findings showing that rural households tend to reduce their labour supply when they expect to receive public transfer (Joulfaian & Wilhelm, 1994). Moreover, when HSNP poor beneficiary households who reside in treated sub-location and are exposed to drought, are 18ppt less likely to receive non-cash transfers than those not exposed to drought and reside in control sub-locations. Taken together, these results offer a precise overview of the behaviour of rural poor households in Kenya: in that they seem to increase labour force participation as opposed to earlier findings that argued that households would rather increase consumption of tobacco and alcohol (Fiszbein & Schady, 2009).

Our paper makes four important additions to the economic literature. To begin with, it contributes to the understanding of the determinants of private transfers received by households in rural Sub-Saharan Africa (SSA). Previous studies (Cox et al., (2004), Cox & Jimenez, (1992) and Jensen, (2004)) have shown that receipt of informal transfer is affected by socio-economic and community level variables. What has been less studied is the contribution of poverty and drought to the crowding out effects literature. In this line, our findings that receipt of private transfers is affected by socio-economic and community characteristics mirror those of Cox et al., (2004), Cox & Jimenez, (1992) and Jensen, (2004). In addition, our findings show that receipt of private transfers is positively impacted by climatic conditions like drought. Moreover, we show that previous high levels of poverty induces households to share (give and receive) private transfers.

The second contribution is the analysis of the behavioural implication of receiving public transfer on demographic compositions and characteristics of rural households (Gerardi & Tsai, 2014; Jensen, 2004; Juarez, 2009; Koh & Yang, 2019). Findings from such studies are often mixed. On the one hand, Gerardi & Tsai, (2014), Jensen, (2004) and Koh & Yang, (2019) found a negative correlation between receipt of public transfer and probability of living with grandchildren. On the other hand, Juarez, (2009) showed that receipt of public transfer increases the probability of living alone for women headed households in Mexico. Jensen, (2004), and Koh & Yang, (2019) showed that receipt of public transfer did not reduce the beneficiary household's labour supply.

Third, our paper extends the discussion around consumption smoothing to support risk pooling following the original work of Morduch, (1995) and Fafchamps, Udry, & Czukas, (1998).

Specifically, we analyse how households smooth their consumption and income using private transfers. Previous literature (See Rosenzweig, 1988) have shown that receipt of private transfers helps poor households offset income fluctuations, and that social networks are key in helping mitigate the associated consumption shortfalls. Rosenzweig & Stark (1989) showed that households experiencing income fluctuations tend to form long distance networks through marriages, which in turn facilitate insurance related income transfers. In addition, Lucas & Stark (1985) observed a positive correlation between exposure to drought, having drought sensitive assets (like livestock) and receipt of remittance. Our finding confirms these previous studies' results on the importance of asset holdings in smoothing consumption in the presence of shocks.

Finally, we provide evidence of crowding out effects from a developing country perspective where such information is hard to find but necessary in helping design policies that account for the socio-economic features of the rural poor in Africa. Our study adds to the growing list of studies from developing countries' perspectives (See Case & Deaton, 1998; Hoddinott, 1992; Jensen, 2004; Juarez, 2009; Kazianga, 2006; Strobbe & Miller, 2011; Strupat & Klohn, 2018; McKernan et al, 2005; Nikolov & Bonci, 2020 for detailed discussion). A common finding in most of these studies is that receipt of public transfer crowds out private transfers. However, we focus on Northern Kenya, a region known for its rich history and culture of gift exchanges. The setting of our study therefore makes our results have an important contribution from a welfare point of view. In addition, most of these previous studies (Hoddinott, 1992; Kazianga, 2006; Strobbe & Miller, 2011) used cross sectional datasets and therefore did not benefit from the time dimension offered by panel data set up. Our paper is among the very few studies that look at the behavioural response of private transfers to public benefits in SSA, alongside other studies mostly conducted in South Africa (Case & Deaton, 1998; Jensen, 2004; Maitra & Ray, 2003) and Ghana (Strupat & Klohn, 2018). Our paper confirms crowding out effects for non-cash but not cash transfers received by poor households in the selected districts in Kenya. We provide a possible explanation for lack of crowding out effects we observe under cash transfer received by households.

The remainder of the paper is organized as follows. In section 3.2 and 3.3, we describe HSNP and present the theoretical framework used in this paper. In section 3.4 and 3.5, we present empirical strategy and data used in the analysis respectively. In section 3.6 and 3.7, we provide covariate balancing tests and discuss our findings and offer suggestive policy directions concerning crowding out effects with reference to Kenya. Section 3.8 and 3.9, we undertake robustness tests to the analysis and a a brief conclusion of our paper.

3.2. Hunger Safety Net Program (HSNP)

HSNP is a social safety net program implemented in Turkana, Marsabit, Mandera and Wajir districts of Northern Kenya. The program started in 2010 and is still ongoing, benefiting over 243,734 households as at May 2019, many (about 60 percent) of whom were female headed households. The program had three main objectives: 1) To reduce poverty, 2) promote asset retention and accumulation, and 3) improve food and nutrition security of households. Indirectly, it was aimed at promoting health, educational uptake, resilience to shocks and access to financial services, among other objectives. The program had two components: A bi-monthly cash transfer and a contingency fund. A cash transfer component started immediately after baseline survey for the households in the treated sub-locations.[50] Initially, cash transfer was fixed at about USD 20 (equivalent to about 12% of household consumption expenditure as at 2010) to each beneficiary household or individuals. The amount was later increased to USD 30 and to a further USD 35 in September 2011 and March 2012 respectively (Merttens et al., 2013). Over the 24 months of the implementation period (i.e., between 2010-2012), most households had received 12 transfers. A second component (i.e., the contingency fund) provides additional cash amount to households when they experience severe or extreme drought conditions. As that, it operated as an insurance scheme for drought. This contingency fund made its first payment (under phase one, between 2010-2012) in 2011.

Program eligibility involved two stages: In the first stage, the HSNP districts were selected based on the 2005/06 Kenya Integrated Household Budget Survey (KIHBS) poverty index.[51]

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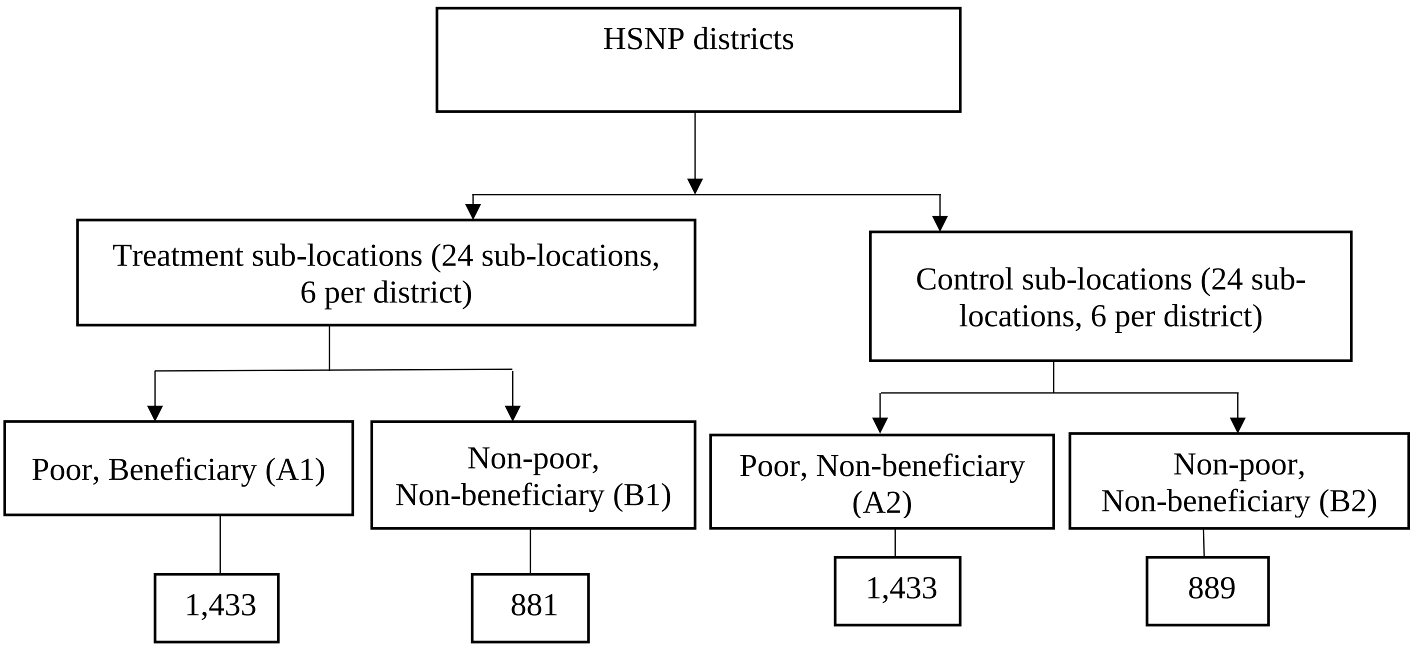
[50] Treated households are those residing in sub-locations selected to start receiving HSNP transfer immediately after baseline survey. These sub-locations continued to receive HSNP transfer until the end of phase one, from where they were joined by households residing in control sub-locations.
[51] According to KIHBS 2005/06, approximately 85 percent of households in HSNP districts are income poor (live below the national poverty line of less than USD 2 per day) while about 54 percent fall under the bottom national decile (Merttens et al., 2013).

In each district, the identification of either treated or control sub-location was done in a public lottery that was attended by both local administration and HSNP officials. On a month-by-month basis, one treated and one similar control sub-location was selected for inclusion. The evaluation was also staggered with baseline survey taking place immediately after targeting. The sequence in which the sub-locations were targeted and surveyed were randomly determined. In the second stage, 66 HSNP beneficiary households were selected using a simple random sampling procedure without replacement. However, HSNP non-poor beneficiaries were sampled from three randomly sampled settlements (i.e., permanent, non-permanent and main) in every sub-location.[52] Based on this procedure, HSNP households can be divided into four categories, as shown in Figure 2: HSNP poor beneficiary and HSNP non-poor, non-beneficiary in treatment sub-locations and HSNP non-poor beneficiary and non-poor non-beneficiary in control sub-locations.



[52] A permanent settlement is a collection of dwellings where at least some households are always resident, and or there is at least one permanent structure. A non-permanent settlement is where there is no permanent structure and thus no person resides there. A main settlement refers to the main permanent settlement in each sub-location and is usually where area local administration was based.

Figure 2: Timelines of the study[53]

In the evaluation sub-locations, targeting process was implemented by HSNP officials. In line with that, a half of sub-locations (i.e., 24 sub-locations) were treated (i.e., those selected to start receiving HSNP after baseline survey) while the rest were control. Assignment of targeting mechanism: either community-based targeting (CBT), social pension receipt (SP), or (3) dependency ratio targeting (DRT) to a given sub-location was randomly done across similar pairs- either to treatment or control sub-location. The aim was to enable comparison of the relative performance of the three mechanisms. For both treatment and control sub-locations, there were equal number of CBT, SP and DR sub-locations. In the HSNP districts, targeting process followed similar structure in treatment and control sub-locations. Where CBT was used, community members identified poor households that would benefit from the program. Under dependency ratio targeting, households were selected if the proportion of its members under the age of 18 or above the age of 55 years old or disabled or critically ill, exceeded a certain set threshold. Where social pension mechanism was applied, all individuals aged above 55 years old were poor beneficiary to receive the transfer. Under CBT and DRT, about 82 and 73.7%, respectively, of registered beneficiaries were women while equal number of men and women were granted with the transfer under social pension. This targeting brings two important facts. First, CBT and DRT increased the bargaining power of women in household decision making processes while SP may have increased the bargaining power of the elderly household members. Secondly, some households received multiple payments per cycle. In fact, about 25% of households selected through SP had two members aged above 55, as at 2010 survey.

Throughout the HSNP 2010-2012 waves, only HSNP beneficiary households in treated sub-locations received the transfer while control households did not until end of 2012. Our identification strategy relies on the staggered rollout and randomized allocation of treatment and control sub-locations into the program to capture seasonal variation and undertake evaluation across households.

[53] In Figure 2, we show the number of households from which information was collected in 2010 and in 2011. It is important to note that in 2012, we do not have non-poor, non-beneficiary households in treated and control sub-locations. This means that our main result is based on HSNP 2010 and 2011 sample only.

3.3. Theoretical framework

Receipt of HSNP may impact private transfer received/given by a household to its network members and this is dependent on the motive of informal transfer.[54] The economic literature argues that households make private transfers for three reasons: altruism, exchange and mutual insurance. An altruism motive of private transfer is driven by the donor's concern about the recipient's utility and because of that, a donor adjusts her transfer behaviour to be consistent with recipient's income levels. This implies that a rise in recipient income will lead to a decline in the amount of private transfer (Barro, 1974; Becker, 1974). If exchange motive prevails, private transfers are considered payments against services provided by the recipient to the donor (Bernheim, Shleifer, & Summers, 1985; Cox, 1987). Therefore, if a recipient's income increases, he is likely to reduce the amount of service offered and therefore a rise in the price of services. In such circumstances, the amount of private transfer received by the recipient is a function of the elasticity of the donor's demand for his services. Under mutual insurance, transfer acts as an insurance and therefore it cushions households against negative shocks (Townsend, 1994). These shocks can take many forms (e.g.: weather change, sudden illness, lack of micro-minerals like Selenium which worsen child health if they exceed recommended consumption threshold, and so forth).

To understand the interaction between public and private transfer, we adopt a Cox private transfer model, an extension of Becker-Barro model (Barro, 1974; Becker, 1974; Cox, 1987; Cox et al., 2004). As a starting point, let's assume that a donor household maximizes her utility (U_d), and that this utility incorporates recipient's utility (V). A donor's utility can be formulated as below (Equation 2.1);

$$U_d = U(C_d, s, V(C_r, s))\ldots\ldots.. \text{(2.1)}$$

[54] Specifically, receipt of HSNP transfer may enable poor households to develop new sources of income because it promotes asset accumulation and retention. In this way, it helps households reduce overreliance on seasonal income sources and therefore strengthens household resilience to shocks and the need to join informal risk sharing schemes.

Where; $C_i, i = r, d$ are recipient (r) and donor (d) consumption levels and s is the amount of services[55] provided by the recipient to donor household. Such a utility function yields three predictions based on the motive of private transfer: either altruism (Barro, 1974; Becker, 1974), exchange (Bernheim et al., 1985) or mutual insurance (Townsend, 1994). If we assume, for simplicity, there are no savings, then the budget constraints for a donor and recipient household can be written respectively as follows in Equations (2.2) and (2.3);

$$C_d = I_d - T \ldots\ldots\ldots\ldots\ldots\ldots \text{(2.2)}$$

$$C_r = I_r + T \ldots\ldots\ldots\ldots\ldots\ldots \text{(2.3)}$$

Where; T is the amount of private transfer (which in this case moves from the donor to the recipient household) and $I_i, i = r, d$ the amount of pre-transfer income for the recipient (r) and donor (d) households, respectively. If the donor is altruistic, then a reduction in her income will directly benefit recipient household. When transfer is exchange motivated however, the sign of the transfer derivative is ambiguously determined. If for some reasons, a recipient household decides to end his services to the donor, he receives no transfer and no payment for services. His utility function can then be represented as $V(I_r, 0)$. Under such conditions, the participation incentive for a donor is represented as ($V(C_r, s) = V(I_r, 0)$). This implies that a donor expects to receive equal compensation so that she can provide a transfer to the recipient. If we assume that a recipient household is rational in his decision, then he will only participate in contracts that give him a benefit that is above what he would have obtained from non-participation (i.e. status quo). This condition is shown mathematically as in Equation (2.4a) below;

$$V(C_r, s) \geq V(I_r, 0) \ldots\ldots\ldots\ldots \text{(2.4a)}$$

Assume further that a recipient household experiences a weather related shock (like drought) which results in losses of his sole asset. Because of this shock, he is likely to receive higher

[55] A service is anything provided by the recipient to a donor for a fee like visitation, companionship or moral support. In some instances, it may be a future financial transfer, so that transfers are treated as a loan. In such a situation, a service can be thought of as '…discounted value of repayments' (Cox et al., 2004).

amounts of private transfers assuming that the donor is altruistically motived. In addition, he may receive insurance from the government in the form of a social safety net to cushion him against the effects of weather shocks. This can be thought of as a disaster insurance. Such transfers by the government are often based on household income levels. Once recipient welfare improves, this public support may be withdrawn. In theory, the amount of private transfer received by a recipient household can be constructed to be a function of household income and other covariates. This private transfer response function can be summarized as below in Equation (2.4b);

$$T_i = f(I_i) + \gamma_i X_i + \varepsilon_i \ldots\ldots\ldots\ldots\ldots\ldots \text{(2.4b)}$$

Where; T_i is the amount of private transfer received by a household; $I_i, i = r, d$ is the pre-transfer income of recipient (r) and donor (d) households respectively while X_i captures the covariates likely to influence the amount of private transfer received. The relevant explanatory variables used in this study include: the log of total household monthly per capita consumption expenditure (adjusted for regional price differences)[56], household size (using OECD modified scale[57]), household head age (in years), age squared, gender of household head (dummy), marital status of household head (dummy), Tropical Livestock Unit (TLU) and specific district dummies to control for district characteristics. The amount of private transfer received responds to pre-transfer income (proxied by receipt of HSNP transfer) following some functional form, $f(\,)$, which may be either linear or non-linear. It is important to note that in this paper, we define our outcome variable as the amount of private transfer received as opposed to net of received and given transfers (as used by Cox, Hansen & Jimenez, 2004) for two reasons. First, to prevent having negative values in the dependent variable which might bias our results. Second, most HSNP poor beneficiary and non-beneficiary households (about

[56] We use hyperbolic sin transformationn whenever we mention log in total monthly per capita consumption expenditure adjusted for regional price differences. The missing values generated by this procedure were replaced by zeros to maintain the sample size. This procedure impact of about 2 percent of our sample.

[57] The Organization for Economic Co-operation and Development (OECD) modified scale assigns a value of one to household head, 0.5 to any other adult household member and 0.3 to every other child (Hagenaars, Klass de-Vos & Zaidi, 1994).

37 percent) are non participant in the private transfer space. For such households, net transfer would be zero and this might significantly impact our regression outputs (see Table 11).

The estimates of transfer response function (Equation 2.4b) are sensitive to estimation strategy applied and how the pre-transfer income enters the equation. In the function, we do not observe a donor's income (I_d) and this causes an omitted variable bias in our model. According to Cox & Rank, (1992) and Cox & Jakubson, (1995), this bias is positive and small and we do not control for it in this study. Our analysis uses different regression specifications to tease out more information from our data as opposed to a single estimation strategy as commonly carried out by earlier studies. Specifically, we start our estimation using Probit and Difference-in-Differences methods. We then extend the analysis to ANCOVA model to offer better estimates of the treatment effects.

3.4. Empirical strategy

3.4.1. Difference-in-Difference method

To test whether participating in public transfer (in the form of HSNP transfer) crowds out private transfers received, we estimate a Difference-in-Differences (DID) method (Wooldridge, 2003). Our identification strategy is that in the absence of HSNP transfers, the amount of private transfers received would evolve the same way for both HSNP beneficiary and control households. We provide covariate balancing tests in Table 10 to check whether the trends in variables evolved similarly over time in the pre-period or baseline period.

Our model can be specified as follows in Equation (2.5a). We provide detailed derivation of a DID approach under Appendix S3.2.

$$T_{ict} = \beta_0 + \beta_1 HSNP_c + \beta_2 Post_t + \beta_3 (HSNP_c * Post_t) + \beta_4 X_{ict} + \vartheta_c + \varepsilon_{ict} \ldots\ldots \text{(2.5a)}$$

Since we have two outcome variables, we estimate two models: first, we run a Probit model (where the outcome variable equals to one if the answer is yes to question 1 and 0 otherwise)[58] for the likelihood of receiving a positive private transfer. This will allow us to determine the extensive margin. Second, we then estimate a Difference-In-Difference (DID) model for predicting the amount of private transfer received, which corresponds to intensive margin[59]. The outcome variable T_{ict} denotes whether a household i in sub-location c and calendar year t, (t =2010, 2011) received private transfer and the amount of private transfer received. $HSNP_{ct}$ is a participation dummy which equals to one if a household received a HSNP transfer and zero otherwise. $Post_t$ is year dummy variable which equals to one if calendar year is 2011 and zero otherwise. β_3 is the DID estimator which captures crowding out effect and thus it represents our main variable of interest. We also include covariates (X_{ict}) household and sub-location specific characteristics (ϑ_c) like drought exposure to control for the heterogeneity and sub-location characteristics. Specific explanatory variables used in this section includes; an indicator variable for HSNP participation (HSNP=1 if a household received a public transfer or lives in treated sub-location); year and district dummies, Tropical Livestock Unit (TLU), household number (OECD scale), respondent age (in years), respondent age (in years) squared, household wealth (in Kenya Shillings); an indicator for respondent marital status (1=Married); an indicator for gender of the respondent (1=Male); Drought exposure (1=if households experience drought at baseline) and finally, logarithm of total monthly per capita consumption expenditure.[60] As we estimate these models on 2010-2011 HSNP poor beneficiary households in treated sub-location only, our result can be thought of as household treatment effects.

Moreover, we estimate sub-location level effects (Equation 2.5b) with an expanded dataset containing four HSNP households: i.e., HSNP poor and non-poor beneficiaries in treated sub-locations and HSNP poor non-beneficiary and non-poor non-beneficary househlds in control sub-locations (See Figure 2 for details). By doing so, we are interested in understanding

[58] The question was framed as follows: “In the past 3 months, has your household received any help (cash, in kind or aid) from any other household as gifts (inclusive from main provider if they don’t live in the household or from any other family member)?”
[59] The follow up question was framed thus: “If the answer to question one above is yes, please indicate the amount (in Kenya Shillings) that you received.”
[60] We applied sine hyperbolic transformation every time we mention logarithm in this thesis (Bellemare & Wichman, 2020). The advantage of this method is that it preserves zero values that would have otherwise been recorded as missing in the case of the traditional natural logarithm.

whether residing in a HSNP treated sub-location irrespective of whether one received HSNP transfer influences the likelihood of receiving a positive transfer (Probit model) and the amount of private transfer received or otherwise (DID model).

The sub-location effects model we estimate is provided below:

$$T_{ict} = \phi_0 + \phi_1 Sub\_loc_{ct} + \phi_2 Post_t + \phi_3 (Sub\_loc_{ct} * Post_t) + \phi_4 X_{ict} + \psi_c + \varepsilon_{ict} \ldots.. \quad (2.5b)$$

Where; Sub_loc_{ct} is a dummy variable which equals one, if a household resides in a HSNP treated sub-location irrespective of whether it received transfer or not. Also, ψ_c is a sub-location dummy that accounts for heterogeneity and community level specific characteristics while ε_{ict} is a mean zero and constant variance error term. ϕ_3 is the DID estimator and it captures the estimate of crowding out effects. The other variables in 2.5b are as defined in equation 2.5a.

As a robustness test, we estimate Analysis of Covariance (ANCOVA) model by pooling observations from survey rounds and using baseline outcome as a control variable. ANCOVA model improves the predictive power of future outcomes especially when autocorrelation is low compared to DID specification (McKenzie, 2012).[61] This is achieved by minimizing error variance through incorporation of additional covariates into the model. This means that estimates of treatment effects obtained from ANCOVA model are more accurate than those derived from DID specification.

[61] When autocorrelation (ρ) is low, it implies that the baseline data does not give precise information about the future values for an outcome. This means that fully controlling for differences in means (at baseline) using DID may overcorrect for differences with limited predictive power. In such a circumstance, ANCOVA adjusts the degree of correction (for baseline differences in means) according to degree of correlation between past and future outcomes actually observed in the data. This means that using ANCOVA gives more power than DID specification when estimating treatment effects with standard economic variables. For example, with a single baseline and follow up and a $\rho = 0.25$, DID requires 60 percent more sample size than ANCOVA to get equal predictive power (McKenzie, 2012).

3.4.2. Analysis of Covariance (ANCOVA) model

The model estimated is shown below (Equation 2.6):

$$y_{ict} = \varphi_0 + \varphi_1 HSNP_i + \varphi_2 y_{ic0} + \varphi_3 S_{t=1} + \lambda_i + \varepsilon_{ict} \ldots.. \text{(2.6)}$$

In the model, y_{ict} is the outcome of interest (in this case private transfer received and or given) by household i residing in sub-location c during survey round $(t = 1)$, with 2010 as $(t = 0)$, 2011 as $(t = 1)$ and 2012 as $(t = 2)$. We first estimate equation 2.6 by using the HSNP 2010-2011 panel sample. y_{ic0} captures baseline outcome $(t = 0)$, for individual household; λ_i captures district fixed effects; $S_{t=1}$ denotes survey wave fixed effects while standard error (clustered at the sub-location level) is captured by $\varepsilon_{ict} \sim N(0, \sigma^2)$.

$HSNP_i$ is an indicator variable which equals 1 if a household received HSNP transfer or lived in HSNP treated sub-location and zero otherwise. In the model, φ_1 is the parameter of interest which identifies the causal effect of HSNP on outcome of interest. Based on the specification, φ_1 can be interpreted in two different ways: either as an Intention to treat (ITT) effects or Local Average Treatment Effects (LATE). For instance, if we denote $HSNP_i$ as assignment to treatment (i.e., receipt of HSNP), we can estimate equation 2.6 using OLS and interpret φ_1 as ITT effects. However, if $HSNP_i$ denotes actual HSNP participation, we calculate average take up at household level, akin to LATE. In this study, we calculate only ITT effects because most (almost 97%) households selected to receive HSNP transfer actually received the transfer. This means that the difference between LATE and ITT effects is minimal.

3.5. Data description

This study employs two datasets. First, our main dataset is from the three waves of Kenya's HSNP panel survey.[62] The second dataset comes from monthly weather data collected by the University of Delaware, Centre for Climatic Research covering 1976 to 2012.[63] These datasets have been used in economic analysis: HSNP data to study the effect of income on food demand

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[62] The HSNP datasets are available at: http://microdata.worldbank.org/index.php/catalog/1917
[63] This data is sourced at: https://www.esrl.noaa.gov/psd/data/gridded/data.UDel_AirT_Precip.html

(Dietrich & Schmerzeck, 2020a) and weather data to study the effect of weather shocks on labour allocation and schooling outcome in India (Ajefu & Abiona, 2019). The implementation of HSNP program lasted approximately 12 months between waves- except for the baseline survey which lasted for two additional months.

Specifically, a baseline survey was undertaken between August 2009 and November 2010 (thereafter 2010) covering 48 randomly selected sub-locations. The selection of the HSNP beneficiary households was also random thereby resulting in perfect mimicry (See Figure 2 for details). A total of 5,108 households were interviewed, of which 60.8 percent were HSNP beneficiary while the rest were spillover households[64]. A first follow up survey (wave 2) was conducted in 2011 covering 4,637 households, implying that the response rate was about 92 percent. Of the re-interviewed 4,637 households, 61.8 percent were HSNP beneficiaries. In the third wave (conducted in 2012), 2,436 households were re-interviewed due to non-random dropping of eight sub-locations (two per district) for security reasons (Merttens et al., 2013). We make use of this third wave to estimate the long run effects of HSNP of the amount of private transfer received.

The survey instrument contained modules like household head characteristics, consumption, transfers and shocks, asset ownership among other topics common in Living Standards Measurement Study (LSMS) household surveys of The World Bank. The instrument was directed at household head or individual (in case of social pension)- i.e., the intended beneficiary of the program.

To capture the amount of private transfer exchanged between households or social network members, respondents were asked to report any amount of private transfer received (vs given) by their households from/to other households residing in the neighbouring sub-locations,

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[64] HSNP beneficiary households (A1 & A2 in Figure 2) are those in treated and control sub-locations who qualified for HSNP transfers, but only treated households started receiving transfers in the first phase (2010-2012). HSNP control households (A2) did not receive any transfers in the first phase and are thus counterfactual of HSNP treated households. Non-poor, non-beneficiary households (B1 & B2), on the other hand, are households in treated and control sub-locations who did not meet HSNP participation criteria but whose information was collected in 2010 and 2011 surveys to aid estimation of general equilibrium effects.

during the 3 months preceding the survey.[65] HSNP questionnaires contained detailed information of private transfer received or given disaggregated by type: either cash, non-cash or in-kind donations. For each transaction, the questionnaire asked households two questions: 1) whether they received a positive private transfers and 2) the value of the private transfer received. For those who answered yes to the first question, a follow up question on the value of the transfer was posed to find out about the types of the transfer received: in cash, non-cash or in kind private transfers.

Attrition: In general, attrition rate between the three surveys was low. For instance, sample attrition between baseline and follow up 1 (wave 1) was 9%, while between follow up 1 and 2 waves was 6%, after taking into account non-random dropping of sub-locations. At the household level, about 4.4% of the household members interviewed during the baseline year (in 2010) were no longer available during the follow up 1 survey. However, 9.5% of the households surveyed during the follow up 1 wave were not available during the follow up 2 wave. At district level, Mandera had the highest attrition rate at 10% (between baseline and follow up 1) while Wajir had the highest attrition rate at 11% between follow up 1 and 2. By treatment status, attrition was highest in treatment compared to control sub-locations: 12 vs 8% respectively. Non-response was due to the nomadic lifestyle of most households in the HSNP districts.

Our second dataset comes from the historical weather data collected by terrestrial air temperature and precipitation: 1900-2014, version 4.01 (Matsuura & Willmott, 2015). This data is gridded on a 0.5 by 0.5 degree resolution around the equator. A detailed description of the procedure used in constructing SPEI (our measure of drought) and the spatial distribution of the weather stations from 1976 to 2012 in Kenya (See Ongudi & Thiam, 2020 for detailed description). Our analysis benefits from spatial distribution of weather stations in constructing our measure of drought. In HSNP districts, 56 weather stations are equally distributed across the area, of which 28 stations are used to generate the SPEI variable. Following Agnew's, (2000) drought classification, we find that HSNP sub-locations were moderately dry (a SPEI

[65] For the amount of food received by the household, the question captured only the value of transfer received with 12 months recall period prior to the survey.

of -0.94 with a standard deviation of 0.97) during the 2010 survey. Comparatively, we find that 2011 period was much drier than that of the 2010 period (i.e., a SPEI of -1.12 with a standard deviation of 1.17 vs -0.94 and a standard deviation of 0.97) respectively. We merge SPEI to HSNP 2010-2012 panel data using sub-location names.

3.6. Baseline randomization and covariate balancing tests

In Table 10, we report the result of the baseline balancing tests from sample mean, standard deviation and p-values for selected household level covariates using HSNP 2010 survey, disaggregated by treatment status (See Appendix S3.1 for description of variables). The first panel shows socio-economic status of the HSNP poor and non-poor beneficiaries and non-beneficiary households, the second panel captures information on informal transfers received, while the third panel captures information about private transfer given to other households. We find that the average size of the HSNP beneficiary households was about 5 members, which is 12% higher than those found in the HSNP non-beneficiary households. Moreover, the HSNP beneficiary households have low levels of consumption, are married and most of these households are male headed compared to the HSNP non-beneficiary households. Most of the HSNP poor beneficiary household heads were on middle aged (the average age is about 52 years) and are therefore not within the productive age brackets of between 25-45 years. Also, there seems to be much variation in age of heads as standard deviation is approximately 16 years. This is consistent with our expectation that in most rural households in Kenya, males are the ones interviewed when data collection takes place. Around 40 percent of HSNP household heads were engaged in livestock herding as main economic activity. This implies that weather related shocks could cause a huge welfare loss to these households. Importantly, only about nine and eight percent of the beneficiary and non-beneficiary households, respectively, had their members participating in formal employment opportunities. This speaks to the limited level of consumption smoothing options available to these households in presence of shocks. In most instances, these households may resort to asset fire sales to cushion themselves against shocks. In terms of asset poverty captured by Tropical Livestock Units (TLU), the difference between HSNP beneficiary households was statistically significant at 10%. This confirms HSNP success in selecting the poorest in the community.

Table 10: Comparing household characteristics at baseline

	HSNP beneficiary		HSNP non-beneficiary	
	Full sample Mean (S.D.)	**Control-Treated households (S.E.)**	**Full sample Mean (S.D.)**	**Control-Treated households (S.E.)**
A: Socio-economic status				
Household size (OECD scale)	4.50 (1.77)	-0.29*** (0.07)	3.98 (1.77)	-0.24** (0.08)
Age of household head (Years)	52.54 (15.68)	0.11 (0.59)	42.66 (14.08)	-1.26* (0.67)
Age squared/100 (Years)	30.06 (16.65)	0.03 (0.62)	20.18 (13.49)	-1.17* (0.64)
Marital status of head (1=Married)	0.68 (0.46)	-0.00 (0.02)	0.82 (0.39)	0.02 (0.02)
Gender of household head (1=Male)	0.68 (0.46)	-0.02 (0.02)	0.81 (0.39)	0.01 (0.02)
Main occupation (1= Herding)	0.41(0.49)	0.03 (0.02)	0.41(0.49)	0.03 (0.02)
Consumption expenditure (KES)	1,770.22 (922.07)	-28.22 (34.45)	2261.97 (1413.83)	-41.70 (67.22)
Tropical Livestock Units (TLU)	7.58 (17.13)	-1.06* (0.64)	9.20 (14.80)	-0.38 (0.71)
Household wealth (KES)	10,051.83 (49,254.32)	-5,629.71** (1,837.39)	24,892.80 (235,622.65)	-5,238.73 (11,203.68)
Labour market participation (1=Yes)	0.09 (0.29)	-0.04*** (0.01)	0.08 (0.26)	-0.05*** (0.01)
B: Private transfer received				
Received any transfer	0.63 (0.48)	-0.01 (0.02)	0.54 (0.50)	0.01 (0.02)
Value of transfer received (KES)	1,711.07 (6,990.01)	5,58.61** (260.97)	1,761.13 (8,641.81)	-1,137.45** (410.05)
Received any cash transfer	0.40 (0.49)	-0.03 (0.02)	0.32 (0.47)	0.02 (0.02)
Value of cash received (KES)	1,284.32 (6,871.00)	478.66* (256.58)	1,415.94 (8,556.59)	-1,177.67** (405.92)
Received any non-cash transfer	0.39 (0.49)	-0.02 (0.02)	0.32 (0.47)	-0.03 (0.02)
Value of non-cash received	235.07 (836.79)	-77.24** (31.23)	168.94 (593.53)	-66.22** (28.18)
Received any in-kind donations	0.12 (0.33)	-0.01 (0.01)	0.11 (0.31)	0.03* (0.01)
Value of in-kind donations received	191.67 (964.70)	-2.72 (36.05)	176.25 (1,302.52)	106.43* (61.89)
Ever received food transfer	0.90 (0.30)	0.03** (0.01)	0.81 (0.39)	0.02 (0.02)
Value of food transfer (KES)	12,079.18 (15,734.58)	272.88 (587.90)	10,293.32 (16,910.50)	-1,070.31 (803.73)
Ever received food Aid	0.84 (0.37)	0.84*** (0.37)	0.71 (0.45)	0.08*** (0.02)
Value of food Aid (KES)	7,086.87 (7,724.59)	911.67** (288.13)	5,619.80 (8,589.63)	136.04 (408.44)

Ever received supplementary feed	0.11	-0.00	0.12	0.01
	(0.32)	(0.01)	(0.33)	(0.02)
Value of supplementary feed (KES)	205.06	-30.75	186.10	35.73
	(1,248.01)	(46.63)	(1,090.32)	(51.84)
Ever received school meals	0.51	-0.05**	0.41	-0.07**
	(0.51)	(0.17)	(0.49)	(0.02)
Value of school meals (KES)	4,787.25	-608.04	4,487.42	-1,242.08*
	(12,839.50)	(479.62)	(13,349.24)	(634.09)
C: Private transfer given				
Given any total transfer	0.31	-0.03*	0.37	-0.04*
	(0.46)	(0.02)	(0.48)	(0.02)
Value of total private transfer given (KES)	519.78	-126.75	702.72	-533.69***
	(3,483.01)	(130.12)	(3,395.60)	(160.97)
Given any cash amount	0.17	-0.01	0.24	-0.03
	(0.37)	(0.01)	(0.43)	(0.02)
Value of cash amounts given (KES)	442.53	99.57	578.19	-458.67**
	(3,450.24)	(128.91)	(3,296.60)	(156.38)
Given any non-cash amount	0.39	-0.02	0.32	-0.03
	(0.49)	(0.12)	(0.47)	(0.03)
Value of non-cash amount given (KES)	77.25	-27.18	124.53	-75.01**
	(479.95)	(17.93)	(519.08)	(24.62)
Observations	**2,866**	**2,866**	**1,770**	**1,770**

Notes: The sample includes HSNP beneficiary (Column 1 and 2) and HSNP non-beneficiary households (Column 3 and 4). HSNP beneficiary households refer to A1 and A2 households while HSNP non-beneficiary households refer to B1 and B2 households (Figure 2)**;** For variable definition, see appendix S3.1. All monetary values are in Kenya shillings (KES); S.D. is the standard deviation; Food transfer is the sum of food aid, supplementary feeding and school meals received by a household in the last 12 months preceding the survey; Control-Treated households refers to the differences in mean values between HSNP poor beneficiary (i.e., A2 verse A1 households) and non-poor, non-beneficiaries (i.e., B2 verses B1 households) in control and treated sub-locations; S.E is the standard error which captures the difference between the mean values of HSNP poor beneficiaries and also between non-poor, non-beneficiary households in treated and control sub-locations for each variable.

In Panel B (Table 10), we capture information on private transfer received. On average, about 63% and 54% of the HSNP beneficiary and non-beneficiary households, respectively, reported having received a transfer in the previous 3 months. On the intensive margin, the HSNP non-beneficiary received higher amounts (1,761 KES versus 1,711 KES) compared to the HSNP beneficiary households. When we disaggregate the private transfers received by type, we find that about 40% of HSNP beneficiary households reported having received cash and non-cash transfers compared to 32% for HSNP non-beneficiary households. At the same time, about 12% of the HSNP households reported having received in-kind donations. On the intensive margin, cash receipts were the most common amongst the HSNP households: they are about 6 times higher than non-cash receipts in the HSNP households and 10 times that of in-kind donations received by the HSNP households. When asked whether they ever received food donation (this includes school meals, food aid, and supplementary meals), about 90% of the HSNP beneficiary households responded positively. The figures are 10% higher than those reported by the HSNP non-beneficiary households. On the value of food donation received, the HSNP beneficiary households received about 17% higher amounts compared to non-beneficiary households (i.e., KES 12,079.18 verses KES 10,293.32) respectively.

In Panel C (Table 10), we summarize the information on private transfers given by HSNP households. About 31% of the HSNP beneficiary households and 37% of the HSNP non-beneficiary households, respectively, made transfers in the past three months. The values of these transfers were higher (by 35%) amongst the HSNP non-beneficiary households compared to beneficiary households (702 KES versus 520 KES), respectively. When we disaggregate private transfers given by types (either cash or non-cash transfers), the HSNP non-beneficiary households are more likely to give than the HSNP beneficiary households: 24% verses 17%. Moreover, the majority of the private transfers was given in the form of cash instead of non-cash amounts. About 40% of the HSNP beneficiary and 32% of the HSNP non-beneficiary households reported having given out non-cash transfers. However, the values of non-cash transfers given were about 6 times lower than the value of cash amounts given out, a trend common amongst both HSNP beneficiary and non-beneficiary households.

Two interesting results emerge from the preliminary analysis of Table 10. First, HSNP treated households seems to have higher number of members eating from the same pot compared to HSNP control households. In general, our sample is well balanced with only 9 out of 26 tests for equality of means rejected. In summary, we conclude that randomization (for HSNP beneficiary households, Table 10) was fairly successful in identifying control groups as true counterfactual for treatment groups except for variables which were used in selecting households like household size and wealth.

3.7. Results and discussions

3.7.1. Household participation and receipt of private transfers

We find evidence (in Table 11) of high dependence on private transfers received amongst rural households in the targeted areas. Approximately 64 percent of households are either recipients only or recipients and givers of private transfers simultaneously in 2010. These findings of a high number of households participating in private transfers are consistent with most studies in developing countries and especially those of Foster & Rosenzweig, (2001). The overreliance on private transfer received provides suggestive evidence of high welfare implication of crowding out of private transfers in these rural households. We observe a six percent reduction in households receiving private transfers between 2010-2011 periods. On average, a large percentage (of about 36 percent) of the HSNP households still received private transfers between these periods, one year after HSNP implementation. As HSNP transfer was a pro-poor program since it targeted the less fortunate, our finding of the high number of recipients is not surprising. Our results are in line with Jensen's, findings (2004) which showed that nearly 43 percent of age qualified South Africans received pension income, a form of public transfer. These are slightly higher (by about nine percent) than those in Burkina Faso (Kazianga, 2006). Interestingly, our results are almost seven times higher than those found in Mexico[66] (Albarran & Attanasio, 2005). The difference in the findings might be attributed to the type of public transfer considered. For Jensen (2004), pension income can be thought of as permanent income while HSNP transfers are transitory income. This implies that the amount of crowding differs depending on whether public transfer is made permanent or kept transitory in nature. Even within the transitory income sources, there seem to be differences depending on whether public transfers are made either conditional or unconditional in nature. It seems that unconditional transfers like HSNP have high levels of impact on the amount of private transfer received compared to conditional transfers.

[66] Albarran & Attanasio, (2005) found that approximately eight percent of the poor but treated households and thirteen percent of control households received private transfers in Mexico.

Table 11: Household participation and receipt of private transfers (HSNP 2010-2011 data)

Private transfer type	2010	2011
Non participants in private transfers (%)	36.65	41.99
As Recipients of private transfers only (%)	32.64	32.91
As donors of private transfers only (%)	6.25	8.06
As both donors and recipients of private transfers (%)	24.50	17.07
Value of private transfer received, if>0	2,709.35	2,401.89
	(8,641.54)	(3,948.99)
2nd percentile value of private transfer received, if>0	2,189.30	2,074.01
	(3,423.01)	(3,465.22)
3rd percentile value of private transfer received, if>0	3,629.56	2,786.00
	(6,497.60)	(4,572.97)
4th percentile value of private transfer received, if>0	5,881.86	3,513.77
	(20,584.92)	(5,009.96)
Value of cash transfer received, if>0	3,206.34	2,478.91
	(10,571.46)	(4,382.95)
Value of non-cash transfer received, if>0	600.46	741.17
	(1,252.99)	(801.52)
Value of in-kind donations received, if>0	1,565.05	2,050.96
	(2,337.19)	(2,213.06)
Households receiving food transfer (%), if>0	56.00	51.00
Value of food transfer received, if>0	13,412.99	15,843.06
	(16,032.11)	(1,5578.68)
Value of supplementary feeding, if>0	1,802.79	2,124.59
	(3,292.55)	(6,044.49)
Value of food aid, if>0	8,469.96	11,430.72
	(7,720.09)	(10,550.58)
Value of school feeding, if>0	9,403.87	8,871.61
	(16,747.99)	(12,671.33)

Source: Authors' calculation using HSNP data; standard deviations are in parenthesis; Quarterly nominal values of cash, non-cash and the total amount of private transfers received are in Kenya Shillings (KES); Values of food transfer, food aid, supplementary and school feeding (in KES) cover past 12 months prior to the survey period; We limit our analysis to HSNP beneficiary households only at baseline and first follow up 1 survey (wave 1); **N=5,732.**

We find that households participating in private transfer space are likely to be recipients, depicting some element of crowding out effects of HSNP transfers. This conjecture might be true because we see a reduction in the amount of private transfer received immediately after the introduction of HSNP. Interestingly, we observe a marginal rise (of about two percent) in the percentage of households donating, one year after the introduction of HSNP transfers. This result reflects the condition that prevailed in 2011, where massive drought ravaged HSNP districts resulting in livestock deaths, food price hikes and human and livestock displacements. This weather induced shock increased vulnerability of rural households, which necessitated calls for supports in forms of private transfers. Finally, we find that, on average, about 36 percent of households did not participate in the private transfer as either giver, receivers or both (Table 11). There are two possible explanations for this. Firstly, the questionnaire focused only on the three months that preceded the survey. Therefore, many households might have received small amounts of private transfers which were reported as zero because they were insignificant. Secondly, in HSNP districts, employment opportunities are limited (only eight percent of households participate in employment work; see Table 10 for details) and so most households are not having relatives or members in other regions affected by shocks.

On average, the amount of private transfer received decreased by about 19 percent between 2010-2012 (Table 11). We observe a similar trend when we disaggregate the amount of private transfer received by quartiles. However, the fourth quartile recorded the biggest decline, of about 26 percent, while there was about a seven percent increase in the amount of private transfer received in the third quartile. A major part of the rise might be due to non-cash transfer received which increased by about 11 percent. These results together reinforce the notion of low earning of rural households and making private transfer an important secondary income source.

3.7.2. Effect of HSNP on informal transfers

Our focus here is to analyse the impact of participating in HSNP on the likelihood of receiving and or giving private transfers and on the amount of private transfer received by and or given to other households. We present our findings in Tables 12, 13 and 14.

In Table 12, Panel A (Column 1 and 3), we show that being HSNP poor beneficiary households in treated sub-locations reduces the likelihood of receiving a cash or non-cash transfer by about 6 percentage points (ppt) compared to households in control sub-locations. This result is not statistically significant at conventional levels (i.e., $P<0.1$) but corresponds to approximately 15 percent reduction relative to the baseline mean.[67] Including the non-poor, non-beneficiary households in the analysis and imposing sub-location level effects, we observe that households in HSNP beneficiary villages have a reduced likelihood of receing cash and non-cash transfer by between 2 and 5 ppt, respectively (Panel B). The 2ppt reduction in cash transfer received corresponds to about 6 percent reduction compared to the baseline mean. This result is not statistically significant at conventional levels (P<0.1) suggesting that spillover effects cannot be excluded. Our findings are similar to ones by Albarran & Attanasio (2005) for Mexico. In turn, participation inin HSNP doess not seem to crowd out in-kind donations received by households independent of the type of empirical model that we employ (Table 12, Column 5). Combining results in a joint analysis we show that HSNP beneficiary households have a reduced likelihood of receiving a private transfer and this reduction is as large as 5 ppt but this result is not statistically significant at conventional levels (P<0.1). This corresponds to approximately 8% of the baseline mean.[68]

On the intensive margin, we find that participating in HSNP lowers the value of private transfer received at a household level by KES 950 compared to control households, i.e. by about 56 percent relative to baseline mean.[69] The value of non-cash transfers received decreased by KES 102. The value of cash and non-cash transfers received is reduced by about 67 and 44%, respectively, compared to their baseline means.

Compared to ANCOVA model (in Appendix S3.3), these results about receipt of a transfer are in similar direction to the ones from the ANCOVA model. However estimates from DID are larger (by about 3 times in absolute terms) in size than those obtained from ANCOVA model. However, this is driven by the receipt of non-cash transfers. We do not find evidence of

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[67] We also estimate the same model under an alternative specification (using the linear probability model) but our results remain similar. These results are not presented here for brevity but is available from the author upon request.
[68] We also estimate the same model under an alternative specification (using the linear probability model). Our results are virtually identical. These results are not presented for the sake of brevity but available from the authors upon request.
[69] To get this estimate, we divide coefficients (in Table 12, Panel A, Column 8) by baseline mean [for example -950.36/1,711.07=-0.56 under DID specification and converting these ratios into percentages. The same approach was used by Nikolov & Adelman, (2019) and (Gulesci, 2020). The full crowd-out effect is a combination of the income effect on the probability of receiving positive transfers and on the amount of transfer received for households receiving positive transfers (McDonald & Moffit, 1980; Juarez, 2009).

crowding-out effects for the receipt of cash transfers. Concerning the value of the private transfer received, the ANCOVA coefficient estimate is more than 5 times smaller in absolute terms reinforcing the importance of conditioning on baseline outcomes when flows are volatile. Despite the reduction in magnitude, the ANCOVA results also identify an overall crowding out effect.

A closer look at our result seem to support altruism motive hypothesis of private transfer and casts doubt on exchange motive. Altruism motive predicts that a dollar increase in recipient's income coupled with the same decrease in donor income should reduce transfer by one dollar. Our household level results are in line with findings from developing countries (Gerardi & Tsai, 2014; Juarez, 2009) that show a reduction in the likelihood of receiving a private transfer to range between 0.48 and 0.55 if a household participates in public transfer program.

Table 12: Estimates of crowding out of private transfer received (HSNP 2010-2011 survey), DID estimates

Variables	**Cash**		**Non-cash**		**In-kind donation**		**Total private transfer**	
	(Yes=1)	**(KES)**	**(Yes=1)**	**(KES)**	**(Yes=1)**	**(KES)**	**(Yes=1)**	**(KES)**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Panel A: Household level effects, N=5,732								
HSNP X Post	-0.06	-861.04	-0.06	-102.40*	0.02	13.07	-0.05	-950.36
	(0.06)	(702.77)	(0.08)	(52.68)	(0.06)	(96.72)	(0.06)	(734.99)
Baseline mean	0.40	1,284.32	0.39	235.07	0.12	191.67	0.63	1,711.07
R-squared		**0.05**		**0.03**		**0.01**		**0.05**
Panel B: Sub-location level effects, N=9,272								
HSNP X Post	-0.02	-882.35	-0.05	-139.75	0.02	14.51	-0.02	-1,007.58
	(0.06)	(806.39)	(0.08)	(52.59)	(0.06)	(67.60)	(0.06)	(818.02)
Baseline mean	0.37	1,334.57	0.37	209.82	0.12	185.78	0.59	1,730.18
R-squared		**0.05**		**0.04**		**0.01**		**0.05**

Source: Robust standard errors (in parentheses) are clustered at the sub-location level; *** p<0.01, ** p<0.05, * p<0.1; Marginal effects (Column 1) are evaluated at sample means; all estimations include indicator variable for HSNP participation (HSNP=1 if a household received a public transfer or lives in treated sub-location); year and district dummies, Tropical Livestock Unit (TLU), household number (OECD scale), respondent age (in years), respondent age (in years) squared, household wealth; an indicator for respondent marital status (1=Married); an indicator for gender of the respondent (1=Male); dependent variable is the probability of receiving a positive private transfer (Column 1, 3, 5 and 7) while for Column 2, 4, 6 and 8, dependent variable are the amount of cash, non-cash transfer and in-kind donations received by households respectively.

In Table 12, we also estimate the sub-location level effects (i.e. equation 2.5b) with a sample of 9,272 households consisting of HSNP treated and spillover households. Here we are interested in the general effect of the programme on private transfer received and or given, and thus we do not distinguish between HSNP beneficiary and spillover households. Our results (in Panel B) show that living in the HSNP beneficiary sub-locations, irrespective of whether a transfer was received or not, reduces the likelihood of receiving positive private transfers by about 2ppt compared to control sub-locations, which corresponds to 6 percent reduction compared to baseline mean (Panel B, Column 1). This result is not statistically significant at the conventional level (P<0.1). Our findings are similar to the ones found by Albarran & Attanasio, (2005) in Mexico, although our percentages are slightly higher. Moreover, we find that residing in HSNP beneficiary sub-locations leads to an about 58 percent[70] reduction in the amount of private transfer received by households relative to baseline mean. This result is not statistically significant at conventional levels (i.e., P<0.1) (Table 12, Panel B, Column 2). The negative sign on coefficients (in Table 12, Panel B) supports altruism motive. Finally, in Table 12, Column 3, the DID specification shows that HSNP did not have significant effects on the likelihood of giving informal transfers to other needy households.

Next, we analyse the effect of HSNP on private transfer received by types: as either cash, non-cash transfers and in-kind donations (Table 12 and Appendix S3.3). On average, receipt of HSNP reduces the likelihood of receiving cash and non-cash transfers by about 6ppt for poor beneficiary households in treated sub-location compared to those in control sub-locations. Although this result is not statistically significant at conventional levels, it represents a 15 percent reduction relative to the baseline mean. For in-kind donations, we find that participating in HSNP transfer for poor beneficiary households increases the value of in-kind donations received by KES 13 compared to households residing in control sub-locations. This value is approximately 6.7 percent compared to baseline mean of in-kind donations received at a household level. On the intensive margin, the value of cash and non-cash transfer received at household levels decreased by KES 861 and KES 102 respectively. This represents about 67 and 44 percent reduction relative to baseline mean of cash and non-cash transfer received.

[70] To get this estimate, we divide the coefficient on HSNP X Post (for example in panel B, Column 8) by the baseline mean [i.e. -1,007.58/1,730.18=-0.58] and convert this ratio into percentage.

At the sub-location level, we find evidence that residing in HSNP treated sub-location reduces the likelihood of receiving non-cash transfer by about 5ppt or 14 percent compared to baseline mean. On the intensive margin, the value of cash and non-cash transfer received reduced by about 66 and 67 percent, respectively, compared to their baseline means. These findings of crowding out effects are repeated under ANCOVA model specifications (see Appendix S3.3). However, we find evidence that the value of in-kind donations received increased by 52 percent if a household resides in HSNP treated sub-locations compard to those in control sub-locations. Compared to ANCOVA estimates, it seems that DID underestimates the level of crowding in effects by more than 10 percent compared to baseline mean under intensive margin and for in-kind donations received.

Using DID and ANCOVA regression results (Tables 12 and Appendix S3.3), we estimate per Kenya shilling crowding out effects (see Appendix S3.10). Since the total value of private transfer received[71] decreased between 2010 and 2011[72], our results do not support existence of per Kenya Shilling crowding out effects for cash, in-kind donations and total transfer received. Specifically, our estimates (under total private transfer received) suggest evidence of crowding in effects in the range of 3.09 and 1.59 for household and sub-location level effects, respectively. This lack of evidence of per Kenya Shilling crowding out effects that has been observed is not unexpected as HSNP transfer amounts are small in value compared to household expenditure. In addition, it was only given to households after every two months which might reduce its influence further.

[71] The types of private transfer are cash, non-cash natures and in-kind donations received by and or given to other households (as provided in the HSNP dataset).

[72] Total private transfer received between 2010-2011 periods decreased from 1,711.07 to 1,218.55 (at a household level) and from 2,894.67 to 2,262.32 at a sub-location level. The DID coefficients are 950.36 and 1,007.58 for household and sub-location level effects respectively. We divide these estimated coefficients with -307.46 and 632.35 (the difference between 2010 and 2011 private transfer received if greater than zero) for household and sub-location amounts respectively to get per Kenya shilling crowding out effects. Our estimates show no evidence of crowding out effects as per Kenya shillings are 3.09 and 1.59 respectively. Our result does not change much even if we exclude in-kind transfers as very few households (about 7.780 percent) reported positive values of in-kind transfers. We followed the same methodology and when estimating the per shilling crowding out effects for private transfer types. Our results support ANCOVA model estimates over DID estimates.

An in-depth analysis of per Kenya Shilling crowding out effects by the type of private transfer received revealed interesting findings though. We note that the per shilling crowding out effects were present in non-cash transfers received at household and sub-location levels. Since non-cash transfers increased marginally (by about Kenya shillings 140 and 174 at household and sub-locatin levels, respectively) between 2010 and 2011, our estimates of per Kenya Shilling crowding out effects are 0.73 and 0.81 at household and sub-location level, respectively. These effects are large and negative implying that receipt of private transfer promptly responds to changes in the income level of households. This response supports altruism motive.[73] In addition, it implies limited distribution effects of public transfer on the amount of private transfer received by poor households. Compared to estimates of the effect of increases in recipient income on the amount of private transfer received from developing countries, our transfer derivative (for non-cash received) is higher than estimates obtained from previous findings. For instance, in South Africa Jensen (2004) find that a rand increase in receipient income is met with about 0.3 reduction in private transfer received. In Peru, Cox and Jemenez, (1992) concluded that remittances (from younger to old family members) would have been 20% higher in the absence of social security pension benefits. In developed countries (like United States of America), Altonji et al. (1997) showed that a dollar increase in adult children's income is met with about 0.08 reduction in private transfer received by the parents. Moreover, Cox and Jakubson (1995) estimate that a dollar increase in public welfare spending results in about 12-cent reduction in private transfer received in the United States of America. The low levels of crowding out observed in developed countries can be attributed to the long history of public transfers which have since replaced private transfers (Cox et al., 2004).

Under cash transfer received, our finding suggests a lack of per Kenya Shilling crowding out effects, but per Kenya Shilling crowding in effects, which range between 0.67 to 1.18 under sub-location and household level, respectively. Finally, we fail to find evidence of crowding out effects at the household and sub-location levels under in-kind donations: i.e., 0.03 verses 0.02, respectively. On average, the per Kenya Shilling crowding out effects are stronger under DID regression compared to under ANCOVA models and for non-cash transfer received

[73] A positive value of a transfer derivative (as we observe under cash, in-kind donation and total private transfers received) suggests the existance of exchange motive of private transfer.

Specifically, DID regression provides estimates of crowding out effects for non-cash transfer received in the range of 0.73 and 0.81 against ANCOVA model estimates of between 0.15 and 0.17. In general, DID specification overstates per shilling crowding in effects compared to ANCOVA model when in-kind donations are considered: i.e., 0.02 and 0.03 verses 0.17 and 0.29 for the sub-location and household level effects, respectively.

We observe that there are two possible explanations for this crowding in effects by cash received. First, our results seem to support the income hiding hypothesis that assumes that women headed households are likely and willing to hide income from family members. If this occurs, then we should expect a positive and significant result when we disaggregate our analysis by gender. We did this and find that women headed households had higher crowding in effects compared to male headed households[74]. This explanation was confirmed by (Jakiela & Ozier, 2016) who also noted that women were willing to pay to hide income from family members. The second explanation is the underreporting of household income in rural areas. It is also possible that the HSNP recipient households under report cash income so that they donate less to other households. In a study conducted in Qatar, (Seshan & Zubrickas, 2017) showed that income under reporting led to low remittance by Indian households to their relatives back in India.

Comparing our findings under household and sub-location level effects confirms two important facts. First, having a clear knowledge of whether a household actually received transfer results in higher estimates of crowding out than when there is noisy information about disbursement of private transfer to their sub-location. This speaks to information rigidity that may exist between recipients and donors. Second, we observe widespread crowding out effects under non-cash transfer in the HSNP sub-locations at both household and sub-location level. This finding supports the known fact that HSNP sub-locations have a rich history livestock sharing (a form of non-cash transfer) that promotes private transfers between community members and relatives.

[74] We do not present these results here for brevity but they are available from the authors upon request.

To summarize this section, the findings show that participation in HSNP transfer crowds out private transfer received by poor households. This effect is more pronounced at a household than sub-location levels, which reinforces the importance of social network in cushioning members from shocks. It also suggest large spillovers from HSNP participation inside a sub-location. Moreover, comparing cash and non-cash transfer received, we find a statistically significant crowding out effects for the receipt of non-cash transfer.

3.7.3. Effect on private transfer given

In Table 13 and in Appendix S3.7.3, we analyse the effect of HSNP on private transfer given to other households. In Panel A, Column 6, we find evidence that participating in HSNP increases the probability of giving cash and total transfer to other households by about 7 and 2 ppt compared to control households (approximately 41 and 9.5 percent compared to baseline mean, respectively). These effects are small and imprecisely estimated pointing rather to a zero effect irrespective of model specification. On the intensive margin, we find that participating in HSNP increases the value of total transfer given to other households by about KES 20 compared to households in control sub-location. This result is not statistically significant at conventional level but represents about 10.4 percent of the baseline sub-location mean (Table 13, Column 6).

Table 13: Effects on private transfer given (HSNP 2010-2011 survey), ANCOVA estimates

Variables	**Cash transfer**		**Non-cash transfer**		**Total private transfer**	
	(1=Yes)	**KES**	**(1=Yes)**	**KES**	**(1=Yes)**	**KES**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Panel A: Household level effects, N=2,866						
HSNP	0.07	13.73	-0.02	7.72	0.02	20.80
	(0.05)	(49.63)	(0.05)	(25.88)	(0.06)	(59.28)
Baseline mean	0.17	135.47	0.34	63.60	0.25	199.07
Adjusted R-squared	**0.19**	**0.01**	**0.20**	**0.02**	**0.21**	**0.01**
Panel B: Sub-location level effects, N=4,636						
HSNP	0.02	40.46	-0.02	12.55	-0.01	53.53
	(0.05)	(123.99)	(0.05)	(24.64)	(0.06)	(128.26)
Baseline mean	0.18	219.50	0.32	83.04	0.26	302.54

Adjusted R-squared	0.17	0.05	0.23	0.03	0.20	0.06

Source: Author's calculation based on HSNP 2010 and 2011 surveys; Robust standard errors (in parentheses) are clustered at the sub-location level; Significance levels *** p<0.01, ** p<0.05, * p<0.1; Marginal effects are evaluated at sample means; quarterly values of private transfers; all estimations include district dummies, household number (OECD scale), household head age, age squared, indicator of marital status (1=married); gender dummy (1=Male), Drought exposure (1=if households experience drought at baseline), Tropical Livestock Unit (TLU) and logarithm of total monthly per capita consumption expenditure, household wealth; dependent variable are the likelihood of giving other households a positive private transfer (Column 1, 3 and 5) and the amount of private transfer given to other households expressed in Kenya Shillings (Column 2, 4 and 6).

At the sub-location level (Table 13 and in Appendix S3.7.3), ANCOVA model estimate shows that residing in HSNP treated sub-location led to about 2 ppt rise in the likelihood of giving out cash transfer compared to those residing in control sub-location. Moreover, we find that the value of private transfer given to other sub-locations increases by KES 54 compared to households in control sub-location. This value is 18 percent[75] of the baseline mean (Table 13, Column 6). These results are not statistically significant at conventional levels (P<0.1). However, when we compare household and sub-location level effects, we find that household level effects are higher than sub-location level effects on intensive but not extensive margins. Taken together, ANCOVA model confirms presence of crowding in effects in HSNP sub-location. When we compare ANCOVA model and DID specification, we find that they both confirm presence of crowding out effects at the sub-location level except for the likelihood of receiveing cash transfer (See Appendix S3.7.3).

3.8. Further analysis and robustness checks

3.8.1. Models without covariates

We also analysed the impact of HSNP on private transfer received using DID specification and ANCOVA model without explanatory variables. We present our findings in Table 14 below (DID specification) and in Appendix S3.5A (for ANCOVA model). Our result show that HSP poor beneficiary households in treated sub-locations reduces the likelihood of receiving cash, non-cash and total private transfer by about 5ppt at a household level compared to those in control sub-locations. This result is not statistically significant at conventional levels. On the

[75] To get this estimate, we divide the coefficient on HSNP (in Table 13, Panel B, Column 6) by the baseline mean [i.e., 53.53/302.54=0.18].

intensive margin, we show that HSNP poor beneficiary households in treated compared to those in control sub-locations observed a reduction in the amount of private transfer received by between 67, 43 and 55 percent for cash, non-cash and total private transfer received, respectively compared to the baseline mean. These results suggest that our estimates are not driven by observable characteristics and thus diminishing the likelihood that te results are driven by differences in unobserved characteristics. This simple comparison further indicates that the randomization was fairly successful in identifying comparable groups.

Table 14: Effects on private transfer received (HSNP 2010-2011 survey), DID estimation

Variables	**Cash**		**Non-cash**		**In-kind donation**		**Total private transfer**	
	(Yes=1)	**(KES)**	**(Yes=1)**	**(KES)**	**(Yes=1)**	**(KES)**	**(Yes=1)**	**(KES)**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Panel A: Household-level effects, N=5,732								
HSNP*Post	-0.06	-861.04	-0.06	-102.40*	0.02	13.07	-0.05	-950.36
	(0.06)	(702.77)	(0.08)	(52.68)	(0.06)	(96.72)	(0.06)	(734.99)
Baseline mean	0.40	1,284.32	0.39	235.07	0.12	191.67	0.63	1,711.07
R-squared		**0.05**		**0.03**		**0.01**		**0.05**
Panel B: Sub-location level effects, N=9,272								
HSNP*Post	-0.02	-882.35	-0.05	-139.75**	0.02	14.51	-0.02	-1,007.58
	(0.06)	(806.39)	(0.08)	(52.59)	(0.06)	(67.60)	(0.06)	(818.02)
Baseline mean	0.37	1,334.57	0.37	209.82	0.12	185.78	0.59	1,730.18
R-squared		**0.05**		**0.04**		**0.01**		**0.05**

Source: Author's calculation based on HSNP 2010 and 2011 surveys; Robust standard errors (in parentheses) are clustered at the sub-location level; Significance levels *** p<0.01, ** p<0.05, * p<0.1; Marginal effects are evaluated at sample means; quarterly values of private transfers; dependent variables are the likelihood of giving other households a positive private transfer (Column 1, 3, 5 and 7) and the amount of private transfer given to other households expressed in Kenya Shillings (Column 2, 4, 6 and 8).

However, we find that participating in HSNP increases the likelihood of receiving in-kind donations by about 1ppt. On the intensive margin, we find that participating in HSNP increases the amount of in-kind donations received by households. The intensive margin result are statistically significant at conventional levels and remain the same under both models. Interestingly, result under sub-location level effects are larger compared to those of household level effects at intensive margin and the reverse is the same at extensive margin. Also, our results remain unchanged when ANCOVA model is estimated (See Appendix 3.9, Table 3.5B).

3.8.2. Heterogeneity across drought exposure levels

We explore the magnitude and significance of crowding out effects when households face weather related shock (in this case drought), using a DID specification.[76] Our analysis is based on the idea that income poor households are likely to exchange (receive and or give) transfers with other households who are affected by uncertainties like droughts. This is done by offering support which can help affected households to smooth consumption and avoid communal actions like expulsion from informal institutions. We find (in Appendix S3.6A, Table S3.6A and Table S3.6B) that the coefficient on drought has a negative sign and it is statistically significant under non-cash transfer received by households. In particular, we show that HSNP poor beneficiary households who experienced drought (at baseline) were about 20 ppt less likely to receive non-cash transfers compared to those who have not been exposed to drought and reside in control sub-locations. Additionally, these drought exposed households are 9 ppt more likely to receive in-kind donations from other households not exposed to drought. At the intensive margin, we find a positive but statistically insignificant increase in the amount received in response to a drought for in-kind donations but not for the cash, non-cash and total sum of private transfer received. Next we turn to the interacted effect between baseline drought exposure, post and HSNP participation (i.e., HSNP*Post*Drought). We find that that HSNP poor beneficiary households exposed to drought (at baseline) receive about KES 1,626 less in total private transfers than households not exposed to drought and reside in control sub-locations. These results are not statistically significant at conventional levels (P<0.1) and hold through even if we alter the drought exposure cut-off points from -0.84 to -1.50[77] (see Appendix S3.6A, Table S3.6B). Thus, even in the case of a severe drought, beneficiaries of HSNP are

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[76] A drought measure we use is covariate shock in that it affects all households of a sub-location equally. We apply a 6-month period (to mimic agricultural season) and classify a sub-location as experiencing drought (i.e., =1 if SPEI<-0.84 and zero otherwise) when Standardized Precipitation Evapotranspiration Index (SPEI) falls below -0.84, akin to Agnew (2000) drought classification. The procedure of construction SPEI is explained in Ongudi & Thiam, (2020). The index averaged -0.94 depicting drought condition in most sub-locations. Approximately 51 percent of households in 2010 we classified as having experienced some drought conditions.

[77] We consider a drought as a covariate shock that affects all households of a village equally. We apply a 6-month period (to mimic agricultural seasons) and classify a village as experiencing extreme drought when the Standardized Precipitation Evapotranspiration Index (SPEI) falls below -1.50 and zero otherwise. This is akin to Dinkelman's (2016) drought classification.

expected to rely on public support reinforcing the earlier established crowding-out effect.

We observe two important trends here. First, when HSNP poor beneficiary households in treated sub-locations are exposed to drought, they are less likely (by between 9 to 18 ppt) to receive cash, non-cash and total private transfers compared to households not exposed to drought and resides in control sub-locations. Secondly, when HSNP poor beneficiary households in treated sub-locations participate in HSNP and were exposed to drought at baseline, they are more likely to receive in-kind donations from other development partners. Specifically, they are 4ppt more likely to receive in-kind donations. On the intensive margin, they receive about KES 33 more compared to households not exposed to drought and did not participate in HSNP (See Appendix S3.6A, Table S3.6A).

3.8.3. Heterogeneity across poverty levels

Next, we explore heterogeneity across treatment effects based on relative poverty levels of households at baseline.[78] We find that the coefficient on whether a household is extremely poor or otherwise is negative but not statistically significant at conventional levels under cash receipt and in kind donations (Appendix S3.8, Table S3.8.1A). Moreover, we show that extremely poor households were about 11 ppt more likelihood to receive non-cash transfers (Appendix S3.8, Table S3.8.1A). These result are statistically at conventional levels. We did not find any systematic differential effects for the receipt of cash transfers in response to being an ultra-poor HSNP beneficiary. On the intensive margin, poor households (at baseline) were more likely to receive cash, non-cash and total private transfer received, although these results are not significant at conventional levels (Appendix S3.8, Table S3.8.1A). The overall crowding out effect of private transfers (i.e., under HSNP*Post*Poor) due to HSNP is found back and also the mechanism it works through, i.e. reductions in cash transfer and in-kind donations received. Importantly, the effects seem to be larger in magnitude implying that the ultra-poor

[78] We considered a household to be extremely poor if its baseline per capita total monthly consumption expenditure (in KES) falls below the sample mean. In our sample, households whose total monthly per capita consumption levels were below KES1,683.44 (the median level of consumption) were deemed extremely poor. Using this classification, we created an indicator variable of household poverty which equals 1 if a household's consumption level falls below this threshold and zero otherwise. In summary, approximately 57 percent of our baseline sample (in this case 2,866 HSNP beneficiary households) were considered extremely poor.

are even less likely to receive private transfers when they are under HSNP compared to other HSNP beneficiaries in control sub-locations. At the same time, we do not identify negative effects on the actual monetary value of the private transfers except under in-kind donations received by households.

With respect to giving out informal transfer to other households, (Appendix S3.8, Table S3.8.2B), we find that being classified as extremely poor and receiving HSNP transfer (i.e., HSNP*Post*Poor) decreases a household's likelihood of giving out total informal transfer to other households. Moreover, we find that poor households who are beneficiaries of HSNP were about 2 ppt more likely to give cash and non-cash transfers to other households compared to households residing in control sub-locations and were not classified as poor at baseline. However, these results are not statistically significant at conventional levels (i.e., $p<0.1$). While this negative effect on the likelihood of giving total private transfers is not reinforced when looking at the monetary amount of the transfer given, it does suggest that the poorest are less in need to insure themselves through private transfers as a result of HSNP (Appendix S3.8, Table S3.8.2B).

3.8.4. Medium term effects on private transfers

As a robustness check, we re-estimate the DID specification (in equation 2.5a) first by total transfer received and secondly, by the types of transfer received by and or given to other households. We use all the three waves of HSNP panel data (i.e. 2010, 2011 and 2012) covering 6,873 households. We present our DID results in Apendix 3.9, Table S3.9A and which can be construed to capture short term effects. First, our results confirm our previous findings that show that participation in HSNP transfers for households residing in treated sub-locations is likely to reduce a household's likelihood of receiving in-kind donations by up to 10 percentage points compared to those in control sub-locations (Panel A)[79]. However, akin to the short term effect with respect to the crowding-out of non-cash transfers we also establish a medium term

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[79] Our results are robust to alternative specification. We estimated a linear probability model (not presented here for the sake of brevity, but available from authors upon request) and results do not change significantly.

crowing-out effect for this type of private transfers. It has a magnitude of 19.99 KES and is statistically insignificant at conventional levels (i.e., P<0.1).

On the intensive margin, we find evidence that confirms that receipt of HSNP transfer led to approximately KES 49 reduction in in-kind donations received by households residing in treated compare to those in control sub-locations. The magnitude, which is statistically significant at conventional levels, is about 26 times the baseline average of in-kind donations received prior to the HSNP implementation.[80] In general, these results provide support for altruism motive but cast doubt on insurance and exchange motives of private transfer.

Secondly (in Table S3.9A, Panel B), we find that in the medium term a household's participation in HSNP transfer increases the likelihood of giving a private transfer (i.e., cash, non-cash and total transfer) by about 4 ppt on average compared to those in control sub-locations. For the intensive margin, we find that HSNP beneficiary households in treated sub-locations reduced the amount of total transfer and cash given to other households by about KES 6 and 1.11 percent, respectively compared to those in control sub-locations. Although these results are not statistically significant at conventional levels (i.e. P<0.1), they represent 35 percent reduction relative to baseline mean value of cash and total private transfer given to other households (Appendix 3.9, Table S3.9A, Panel B).

3.8.5. Behavioural implications of receiving HSNP transfers and crowding out effects

Past evidence suggests that estimates of crowding out effects are sensitive to socio-demographic characteristics of the respondents. For example, Cox et al., (2004) and Juarez, (2009) found strong crowding out effect amongst low income households. In Mexico, Juarez, (2009), found a positive and significant effect of receipt of pension and shared living amongst women headed households, highlighting the importance of gender. On earnings, Holtz-Eakin, Joulfaian, & Rosen, (1993) and Joulfaian & Wilhelm, (1994) noted that heirs tend to reduce their labour supply once they receive inheritance from family members. Therefore, there is no uniformity of findings on these relationships and the results mostly vary by study locations. In

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[80] We estimated this value as -48.97/191.67=0.26. the -48.97 is from Table S3.9.1A (column 6) while 191.67 is from Table 10.

this section, we test whether our estimates of crowding out effects are sensitive to demographic characteristics (especially household size, employment participation, household earnings) using out HSNP 2010-2012 dataset. Our result is shown in Table 15 below.

Table 15: Response of households to receipt of HSNP transfers (HSNP 2010-2012 sample)

Variables	**Co-residence**	**Labour supply (1=Yes)**	**Off-farm earnings**	**Farm earnings**	**Total earnings**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
HSNP X Post	-0.15**	0.03	-4.01	-1.03	-5.04
	(0.07)	(0.04)	(6.24)	(1.91)	(6.51)
R-squared	**0.17**		**0.08**	**0.19**	**0.12**

Source: Author's calculation based on 2010-2012 HSNP sample, Robust standard errors (in parentheses) are clustered at the sub-location level; *** p<0.01, ** p<0.05, * p<0.1; Marginal effects (column 2) are evaluated at sample means; annual nominal values of household income were converted to monthly nominal values and then deflated using Kenya's Consumer Price Index; regressors included in the regression but not shown here for brevity include a dummy for HSNP treated which equals 1 if household received a transfer and 0 otherwise, Tropical Livestock Unit, district and year dummies, household head age (in years), age (in years) squared, a dummy for gender (1=Male), a dummy for marital status (1=married); dependent variable are household size (OECD scale) (Column 1), household participation in employment (Column 2), off-farm earnings or income sources (Column 3), farm earnings or income sources (Column 4) and total earnings (Column 5) respectively, Column 2 present marginal effects; **N=4,872**.

The first and most important response to increased income amongst households, is to allow more relatives and children from other family members to visit and stay with well-off households, thereby increasing household sizes. This reinforces the child fostering hypothesis that has been shown to drive private transfers in the developing countries (Case & Deaton, 1998). This is especially so because in most developing countries, social security is non-existent to provide all vulnerable households with the care that is required to guarantee good nutrition and general education to their children. It is therefore a common practice for elderly parents to share a home/house with their adult children to ease care or richer households to support children from less fortunate family members to allow them attend distant school. These arrangements can be thought of as forms of private transfer. Alternatively, if households are constrained by high migration cost, receipt of HSNP transfer can help beneficiaries overcome these challenges. Such migration constraints are well documented in Indonesia (Besley et al., 2014). If such conditions exist, our results would be biased. To test for these hypotheses, we estimate a regression equation with household size (in OECD scale) as dependent variable and other covariates as shown in Table 15. Our difference in difference estimate shows (Table 15, Column 1) that HSNP beneficiary households residing in treated sub-locationshad smaller household sizes (by about 15 percentage points) household sizes compared to HSNP beneficiary households in control sub-locations. These findings are statistically significant at a conventional level ($P<0.1$) and support the migration cost hypothesis highlighted above. In general, we conclude that participating in HSNP transfer induced changes of household structure (i.e., it reduced the size) in general for HSNP poor beneficiary inf treated compared to those in control sub-locations. Here, our result mirrors those of Gerardi & Tsai, (2014) in Taiwan who showed that receipt of allowance increased a household probability of living with parents, leading to an increase in household size.

Second, members of HSNP beneficiary households may reduce their labour market participation when they start receiving or expect to receive public transfers. This is possible because income from public transfer may raise the demand for leisure amongst beneficiary and non-beneficiaries indirectly. To test for this hypothesis, we ran a regression specification where our dependent variable is an indicator variable that depicts whether a household member participates in labour market and included other covariates as shown in Table 15. In column 2, Table 15, we show that the contray is the case. Labor supply increases among beneficiary households implying that households do not substitute work for leisure although their incomes have improved. Nevertheless, this result is not statistically significant at conventional levels (i.e., $p<0.1$). This finding can curtail concerns about negative repercussions on the labor market of developing countries from social safety net programs. Yet, effects might work through the income channel, which has the potential to bias our crowding-out effects. We identify negative yet statistically insignificant impacts across income categories (Table 5, Columns 3-5). These results are similar to the ones found by Gerardi & Tsai (2014) for Taiwan and Jensen (2004) for South Africa (for female sub-sample only) suggesting that social safety net programs in developing countries should not be abandoned due to the potential negative implications they might have on labour market, a finding that is at odds with the common substitution effect that is assumed to prevail between leisure and labour.

The economic theory holds that rational households usually substitute work for leisure as income increases. Although HSNP households are poor, less educated and with high job skills mismatch, they are still interested in participating in the labour market even if it is in the informal sector. This drive might be brought about by the urge to diversify household income sources. This might be associated with the information friction concerning urban income amongst the rural poor households. According to Baseler (2020), potential rural migrants suffer from information asymmetry concerning how much urban residents earn. In most instances, urban income earners underestimate their true wages when asked by their rural network members. This information inaccuracy enhances urban migrant's strategic motives to reduce remittance obligations. This is against Holtz-Eakin et al., (1993) and Joulfaian & Wilhelm, (1994) findings that heirs to an inheritance income reduced their labour supply.

Finally, an important concern is that HSNP beneficiary households might reduce their labour supply or work less hours due to high demand of leisure occasioned by increased income. If this happens, we expect household earning potential to reduce, thereby biasing our crowding out effect estimates. To explore these possibilities, we run three regressions: one with total household income, another with off-farm earnings and finally, a third with farm income, as dependent variables. In all these regressions, we included covariates used in the DID estimation (Table 15, Column 3-5). We find weak evidence that supports the assumption that receipt of public transfer reduces household income: our coefficient of interest (DID estimate) is negative, small in magnitude and not statistically significant at conventional levels ($P<0.10$). These results are similar to the ones found by (Gerardi & Tsai, 2014) for Taiwan and Jensen (2004) for South Africa.

3.8.6. HSNP income and household expenditure allocation

How should a household allocate HSNP transfer (a form of transitory income) into its different expenditures portions? This is an important question because most HSNP recipients are income poor and if HSNP income is considered as additional household income, then we expect it to push household spending budgets up, especially those related to food. To test this hypothesis, we regressed household expenditures (in this case food, non-food, education, health and total household expenditures) on total pre-transfer household income and on HSNP income (proxied by the interaction between HSNP and Post) plus other covariates (see Table 16 for these explanatory variables). There are three possible scenarios from these regression outcomes. First, if the coefficient on HSNP income is greater than those of pre-transfer income, then it seems that HSNP households favour food over other expenditures. Second, if the coefficient on HSNP income is less than those of pre-transfer income, it implies that HSNP income is being directed to other household uses. Third, if there is equality in the size of coefficient from HSNP and pre-transfer incomes, then it implies that households treat HSNP income like any other household income sources. This implies that it should be used to spur household expenditures and especially those related to food. Our result is shown below (Table 16).

Table 16: Allocating HSNP transfer and pre-transfer income in a household (HSNP 2010-2012)

Variables	**Food**	**Non-food**	**Education**	**Health**	**Total**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Ordinary Least Squares (OLS) regression					
HSNP X Post	221.19**	327.90	-9.00	13.18*	308.12**
	(94.36)	(327.72)	(39.84)	(6.81)	(116.56)
Farm income	-0.81	9.51	0.30	0.12	-0.84
	(0.97)	(6.99)	(0.45)	(0.13)	(1.67)
Non-farm income	5.22***	22.99***	1.57***	0.16***	9.80***
	(1.26)	(4.90)	(0.51)	(0.05)	(2.28)
R-squared	**0.24**	**0.46**	**0.10**	**0.04**	**0.34**

Source: Author's calculation based on HSNP 2010 and 2012 samples, Robust robust standard errors (in parentheses) are clustered at sub-location level; *** p<0.01, ** p<0.05, * p<0.1; Post is a dummy variable which equals 1 if HSNP data was collected in 2012 and zero otherwise; HSNP is a dummy variable which equals 1 if a household lives in HSNP treated sub-location and zero otherwise; farm and non-farm income sources are continous variables; annual nominal values of household income (in Kenya Shillings) were converted to monthly nominal values and then deflated using Kenya's Consumer Price Index; regressors included in the regression but not shown here for brevity include Tropical Livestock Unit, district dummies, household head age (in years), age (in years) squared, a dummy for gender (1=Male), a dummy for marital status (1=married); **N=4,872.**

We find suggestive evidence that HSNP poor beneficiary households in treated sub-locations favour food over other household expenditures (like education and health) compared to those in control sub-locations. This result is commonly found when household income is controlled by women. This is evidenced by the large marginal propensity to spend on food out of HSNP transfer than estimated marginal propensity to spend on food out of pre-transfer income. Here our result is contrary to Case & Deaton, (1998) findings that argue that pension income was directed to other uses which may include non-food expenditures. A possible explanation might be that pension income is likely to be permanent while HSNP transfer is more transitory in nature. The implication of this finding is that poor households respond differently to permanent and transitory income sources. In Column 2, we re-estimated the same model but with outcome variable as non-food expenditures.[81] We show that HSNP poor households in treated sub-locations had higher preference for non-food expenditures than all other household expenditures compared to those in control sub-locations. However, this result is not statistically different from zero. In column 3, we show that HSNP poor beneficiary households in treated sub-locations increase expenditure in healthcare by about 13 percent compared to those in control sub-locations. This result is statistically significant at five percent. In general, the same result of higher marginal propensity to spend on food expenditure out of HSNP transfer than that of pre-transfer income is replicated across all household expenditures. An interesting result is that households do not seem to use HSNP transfer to increase education investment. This result is consistent with the nature of the targeted communities whose livelihood is mainly dependent on pastoralism. Specifically, young male children often favour herding to getting an education. Lastly, households do not seem to share HSNP transfer with other households but divert it to other uses, probably to meet urgent expenditures.

3.9. Conclusion

The goal of this paper has been to test whether receiving a HSNP transfer crowds out private transfer arrangements that have existed for years in rural areas of Kenya. We exploit a large panel dataset of households who randomly received public transfers (in the form of HSNP transfer) in Turkana, Wajir, Marsabit and Mandera districts, Kenya. This paper documents two important facts that are consistent with previous studies. First, we show that receipt of public transfers reduces the likelihood of a household to receive private transfers (i.e., cash and non-cash) by approximately 6 percentage points compared to households in control sub-locations. Although this result is not statistically significant at conventional levels (i.e., $P<0.1$), it corresponds to approximately 15 percent reduction relative to the baseline mean. Including the non-poor, non-beneficiary households in the analysis and imposing sub-location level effects, we observe that households in HSNP beneficiary villages have a reduced likelihood of receing

[81] These are non-durable goods which are purchased by households. The survey records their purchases over one-week (e.g., transport), one-month (e.g., personal hygiene) and six months (e.g., house utensils, clothes) periods.

cash and non-cash transfer by between 2 and 5 ppt, respectively. The 2ppt reduction in cash transfer received corresponds to about 6 percent reduction compared to the baseline mean.

Second, we find evidence that receiving public transfers (proxied by receipt of HSNP transfer) significantly reduces the amount of private transfer received by about 56 percent compared to baseline mean of private transfer received, a result that reinforces early findings on the interaction between private and public transfers in poor households. Especially, we identify crowding-out effects for the receipt of non-cash transfers but not for cash transfers. Our estimate of the per Kenyan Shilling crowding-out effect ranges between 0.73 and 0.81 for the recipt of non-cash transfers at the household and village levels, respectively. Third, we analysed the effect of HSNP in presence of drought. We show that HSNP poor beneficiary households who experienced drought (at baseline) were about 20 ppt less likely to receive non-cash transfers compared to those who have not been exposed to drought and reside in control sub-locations. Additionally, these drought exposed households are 9 ppt more likely to receive in-kind donations from other households not exposed to drought

In addition, participation in a public transfer programme does not seem to reduce labour market participation and this has been confirmed by our various robustness tests. These findings have important implications for the design of and efficacy of social programs. In that, they offer support for the existence of strong relationship (of income sharings) amongst rural poor households. This means that evaluations of social transfers should take into account these spillover effects to avoid overstating the distributional impacts of these programs. Finally, we find suggestive evidence that HSNP poor beneficiary households in treated sub-locations favour food over other household expenditures (like education and health) compared to those in control sub-locations.

The findings from these studies support the altruism motive of private transfers brought into the economic literature by Gary Becker a few decades ago (Becker, 1974). Therefore our findings put a doubt on the exchange motive of private transfer received in Kenya. This finding suggest that once a government steps in as social securer it better has a long-term commitment since households are taken out of their traditional structures of exchange and have to rely on the government in times of shock as our drought exposure analysis has shown. Yet, we also find initial evidence that the crowding out effects in private transfers might fade in the longer run. The results in this paper makes an important contribution to the literature of interhousehold behaviour and crowding out effects. While the results are for Kenya, the information is likely to be of importance to public transfers commonly used to support poor households in various Sub-Saharan African countries.

3.10. Areas for further research

A fruitful extension of this study would be to analyse projects that have existed for several years (probably over five years) to determine the long term implications of crowding out. In line with that, studies should try to compare findings from cash transfers and other forms of social protection like school feeding programs that are not given in monetary terms. Secondly, our study makes use self reported information (i.e., the amount of private transfer received or given to other households) to test crowding out effects of private transfer by public transfers. In a population where majority of the population are illiterate and poor, self reported information might not be accurate. This might have an implication on the final results obtained. Although, we have done numerous robustness checks that have shown limited effect of self-reported information on our result, future studies should use administrative data (especially those obtained from *MPESA*[82] financial statement) that capture specific amount of private transfer received or given to other households. Results from such analysis should be compared with self-reported estimates used in this study. Finally, future work should get information concerning pre-transfer income of rural households. Using pre-transfer income sources will allow estimation of non-inear models similar to those used by Cox et al., (1987).

[82] This is a mobile money transfer platform being used in Kenya. It is promoted by telecommunication company called SAFARICOM.

APPENDICES TO CHAPTER THREE

APPENDIX S3.1: LIST OF VARIABLES

- Household wealth – Sum of all household assets related to production, mobility, general furniture, information access and durable assets owned by a household. Production goods include animal cart, Hoe, water drum, plough, Wheelbarrow, Sickle, Pix axe, Axe, fishing net, panga, spade. Household goods includes stove, leather bead, mattress, metal box, Gourd, mosquito net, bucket, traditional stool, mat, Jerry can, Skin, pelts and hides; household durable goods include mobile phone, radio, television, computer, wristwatch, paraffin lamp, jewelry, satellite box, washing machine; household mobility goods include car, motorcycle, bicycle, spear or bow.
- Consumption expenditure – Total household monthly consumption expenditure per adult equivalent using OECD modified scale. The Organization for Economic Co-operation and Development (OECD) modified scale assigns a value of one to household head, 0.5 to any other adult household member and 0.3 to every other child (Hagenaars, Klass de-Vos & Zaidi, 1994)
- Age of the respondent – age of household head (years) as reported by the respondent
- Marital status of the respondent – a dummy variable which equals one if a household reported as having been married
- Gender of the respondent – a dummy variable which equals one if it's a male and zero otherwise
- Main occupation – a dummy variable which equals one if a household main economic activity is herding livestock
- Tropical Livestock Unit (TLU) – Is asset-based poverty measure tied to the number of livestock (cattle, goat, sheep, donkey/Ass/Mule, camel) owned by a given household. We assign a value of one for every cattle owned: 0.1 for Donkey/Ass/Mule, 0.1 for Sheep or Goat 0.01 for Poultry and 1.4 for Camel. We summed these values to create a composite index called the Tropical Livestock Unit (TLU) (Lybbert, Barrett, Desta, & Coppock, 2004).
- Received any private transfer – a dummy variable =1 if the respondent household reported having received ay transfer in the last 3 months prior to the survey.

- Value of transfer received – monetary value of private transfer received I cash, non-cash or in-kind donation by a respondent's household during the past 3 months prior to the survey.
- Received any cash transfer – a dummy variable =1 if a respondent's household reported having any cash transfer from other households in the previous 3 months to the survey.
- Value of cash received – monetary value of cash transfer received by a respondent's household during the previous 3 months prior to the survey.
- Received any non-cash transfer – a dummy variable =1 if a respondent's household reported having any non-cash transfer from other households in the previous 3 months to the survey.
- Value of non-cash received – monetary value of non-cash transfer received by a respondent's household during the previous 3 months prior to the survey.
- Received any in-kind donations – a dummy variable =1 if a respondent's household reported having any in-kind donations from other households in the previous 3 months to the survey.
- Value of in-kind donations received – monetary value of in-kind donations received by a respondent's household during the previous 3 months prior to the survey.
- Given any private transfer – a dummy variable =1 if a respondent's household reported having given any private transfer from other households in the previous 3 months to the survey.
- Value of private transfer given – monetary value of private transfer given by a respondent to other households during the previous 3 months prior to the survey.
- Given any cash transfer – a dummy variable =1 if a respondent's household reported having given any cash transfer from other households in the previous 3 months to the survey.
- Value of cash transfer given – monetary value of cash transfer given to other household during the previous 3 months prior to the survey.
- Given any non-cash transfer – a dummy variable =1 if a respondent's household reported having given any non-cash transfer to other households in the previous 3 months to the survey.
- Value of non-cash given – monetary value of non-cash transfer given by a respondent's household to other households during the previous 3 months to the survey.

APPENDIX S3.2: A DIFFERENCE-IN-DIFFERENCES (DID) SPECIFICATION

To estimate the crowding out effect, a simpler method is to compare the average amount of private transfer received by HSNP treated and control households. The identifying assumption being that in the absence of HSNP transfer, the amount of private transfer received by HSNP treated and control households would evolve the same way. This means that the difference can only be attributed to participating in a public transfer programme. We assume the existence of two groups of households; either treated or control. We specify a linear regression (equation 1ab) to measure the average effect of receiving HSNP transfer on the amount of private transfer received as below.

$$T_{ic} = \beta_0 + \beta_1 HSNP_{ic} + X_{ic}\beta_2 + \varepsilon_{ic} \dots \dots .. (1A)$$

Where; T_{ic} is the amount of private transfer received by a household i in sub-location c; $HSNP_{ic}$ is a treatment dummy which equals to one if a household received a transfer and zero otherwise. X_{ic} is a vector of demographics, household head characteristics and community level variables which might influence the amount of private transfer received. Inclusion of these covariates allows us to control for factors that may cause differentials in the amount of private transfer received across these two groups of households. Lastly, ε_{ic} is the white noise. To incorporate regional differences into our equation 1A above, we decompose our error term into two components. The first component captures the variation arising from regional differences and this is common to all households living in a given locality or sub-location. The second component captures the variation arising from random shocks. From (1A), the expected value of HSNP treated and control households can be derived as follows.

$$E[T_{ic}|HSNP_{ic} = 1] = \beta_0 + \beta_1 + X_{ic}\beta_2 \dots \dots \dots . (2A)$$

$$E[T_{ic}|HSNP_{ic} = 0] = \beta_0 + X_{ic}\beta_2 \dots \dots \dots \dots .. (3A)$$

From $(2A)$ and $(3A)$, it follows that the average intended treatment of the treated effect can be written as (Equation 4A).

$$E[T_{ic}|HSNP_{ic} = 1] \text{-} E[T_{ic}|HSNP_{ic} = 0] = \beta_1 \dots \dots (4A)$$

This simple model can be extended to a panel data framework by incorporating (into equation 1A) a time dimension ($i.e.; Post_t$) to take into account differences in time (t) periods of the surveys. However, this is only possible under two specific conditions: (1) if baseline and follow up survey datasets are available and (2) are comparable, given the similarity of covariate balancing test. If not, the above equation should be estimates using Ordinary Least Squares method. Our dataset allows for this panel data framework extension. Therefore, our equation can be summarized as below.

$$T_{ict} = \beta_0 + \beta_1 HSNP_{ct} + \beta_2 Post_t + \beta_3 (HSNP_c * Post_t) + \beta_4 X_{ict} + \vartheta_i + \varepsilon_{ict} \ldots.(5A)$$

In $(5A)$, the estimate of parameter β_3 is the Difference-In-Difference (DID) estimator which captures the impact of HSNP participation on the amount of private transfer received by a household. This can be summarized as.

$$\{E[T_{ict=1}|HSNP_{ic} = 1, Post_{ic} = 1] - E[T_{ict=1}|HSNP_i = 0, Post_t = 1]\} -$$
$$\{[E[T_{ict=0}|HSNP_{ic} = 1, Post_{ic} = 0]] - [E[T_{ict=0}|HSNP_{ic} = 0, Post_{ic} = 0]\} = \beta_3 \ldots\ldots..(6A)$$

In $(6A)$, $T_{ict=1}$ and $T_{ict=0}$ denotes the amount of private transfer received by HSNP treated and control households or HSNP treated and control sub-locations in the case of sub-location level effects respectively. This is the final model we estimate in this paper. The beauty of writing equation $(5A)$ as above is that it allows for estimation of household level fixed effects, because $(HSNP_{ci} * Post_t)$ varies with time. In all these discussions, we have assumed that there are no or small amount of spill overs. Alternatively, the reader can rely on other conditions (see Albarran and Attanasio, 2002 for this discussion).

APPENDIX S3.3: EFFECT ON PRIVATE TRANSFER RECEIVED, BY TYPES

Here, we present the results of our main regression (i.e., using HSNP 2010-2011 sample), first by the types of private transfer received and then by total value of private transfer receive. We show ANCOVA coefficients (Table 12).

Table S3.3: Estimates on private transfer received (HSNP 2010-2011), ANCOVA estimates

Variables	**Cash**		**Non-cash**		**In-kind donations**		**Total transfer**	
	(Yes=1)	**(KES)**	**(Yes=1)**	**(KES)**	**(Yes=1)**	**(KES)**	**(Yes=1)**	**(KES)**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Panel A: Household level effects, N=2,866								
HSNP	-0.02	-106.14	-0.02	-36.62	0.03	19.80	-0.04	-125.03
	(0.04)	(178.16)	(0.05)	(38.91)	(0.02)	(50.81)	(0.04)	(206.31)
Baseline mean	0.36	901.26	0.34	249.30	0.03	67.98	0.51	1,218.55
Adj. R-squared	**0.08**	**0.08**	**0.20**	**0.05**	**0.04**	**0.01**	**0.14**	**0.07**
Panel B: Sub-location level effects, N=4,636								
HSNP	-0.01	-23.39	-0.03	-42.41	0.00	12.57	-0.02	-56.87
	(0.04)	(108.08)	(0.05)	(39.95)	(0.02)	(36.41)	(0.04)	(140.72)
Baseline mean	0.35	789.17	0.32	242.50	0.03	66.79	0.49	1,098.46
Adj. R-squared	**0.09**	**0.07**	**0.24**	**0.05**	**0.03**	**0.02**	**0.17**	**0.06**

Source: Robust standard errors (in parentheses) are clustered at the sub-location level; significance level, *** p<0.01, ** p<0.05, * p<0.1; Marginal effects (Column 1) are evaluated at sample means; all estimations include indicator variable for HSNP participation (HSNP=1 if a household received a public transfer (Panel A) or residing in treated sub-location (Panel B)); district dummies, Tropical Livestock Unit (TLU), household number (OECD scale), respondent's head age (in years), respondents age (in years) squared, household wealth (in Kenya Shillings); an indicator for household head marital status (1=Married); an indicator for gender of household head (1=Male); dependent variable is the probability of receiving a positive private transfer (Column 1, 3, 5 and 7) while dependent variable (for Column 2, 4, 6 and 8) are the amount of cash, non-cash transfer and in-kind donations received by households respectively.

We show that participation in HSNP reduces the likelihood of a household receiving cash and non-cash transfer amounts by about 4 ppt. These coefficients are slightly higher compared to those obtained using ANCOVA models although the negative direction of transfer remains the same. At intensive margin, participating in HSNP reduces the amount of cash, non-cash transfer received. These results hold under sub-location level effects although the results are smaller than those under household levels. In general, we find that participation in public transfer decreases the likelihood and the amount of private transfer received. Therefore, we confirm altruism motive for cash and non-cash transfer received.

APPENDIX S3.5A: EFFECT ON PRIVATE TRANSFER RECEIVED, ANCOVA MODEL ESTIMATED WITHOUT COVARIATES

Table 3.5B: Effects on private transfer received (HSNP 2010-2011 survey), ANCOVA model

Variables	Cash		Non-cash		In-kind donation		Total private transfer	
	(Yes=1)	(KES)	(Yes=1)	(KES)	(Yes=1)	(KES)	(Yes=1)	(KES)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel C: Household level effects, N=2,866								
HSNP	-0.02	-80.32	-0.02	-34.84	0.00	24.77	-0.05	-94.05
	(0.05)	(214.17)	(0.05)	(39.32)	(0.02)	(46.65)	(0.05)	(228.93)
Baseline mean	0.36	901.26	0.34	249.30	0.33	67.98	0.51	1,218.54
Adjusted R-squared	**0.03**	**0.05**	**0.18**	**0.03**	**0.03**	**0.01**	**0.10**	**0.03**
Panel D: Sub-location level effects, N=4,636								
HSNP	-0.01	40.66	-0.03	-40.85	0.00	15.76	-0.03	10.55
	(0.09)	(137.54)	(0.05)	(42.05)	(0.02)	(34.42)	(0.04)	(156.10)
Baseline mean	0.35	789.17	0.32	242.50	0.03	66.79	0.49	1,098.46
Adjusted R-squared	**0.04**	**0.04**	**0.22**	**0.04**	**0.03**	**0.02**	**0.14**	**0.03**

Source: Author's calculation based on HSNP 2010 and 2011 surveys; Robust standard errors (in parentheses) are clustered at the sub-location level; Significance levels *** p<0.01, ** p<0.05, * p<0.1; Marginal effects are evaluated at sample means; quarterly values of private transfers; dependent variables are the likelihood of giving other households a positive private transfer (Column 1, 3, 5 and 7) and the amount of private transfer given to other households expressed in Kenya Shillings (Column 2, 4 6 and 8).

APPENDIX S3.6A: EFFECTS ON PRIVATE TRANSFER RECEIVED, BY DROUGHT EXPOSURE LEVELS

Table S3.6A: Effects on private transfer received, DID estimates

Variables	**Cash transfer**		**Non-cash transfer**		**In-kind donation**		**Total transfer**	
	(1=Yes)	**KES**	**(1=Yes)**	**KES**	**(1=Yes)**	**KES**	**(1=Yes)**	**KES**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
HSNP	0.04	373.41	-0.02	66.87	-0.00	62.36	0.00	502.65
	(0.05)	(472.18)	(0.04)	(54.81)	(0.03)	(68.90)	(0.05)	(506.11)
Post	-0.13**	-775.34*	-0.19***	-51.79	-0.05	-80.40	-0.23***	-907.53**
	(0.05)	(413.25)	(0.06)	(57.77)	(0.06)	(68.94)	(0.06)	(418.20)
HSNP*Post	-0.00	27.48	0.03	-28.14	-0.00	8.52	0.01	7.86
	(0.08)	(576.65)	(0.08)	(79.93)	(0.07)	(93.57)	(0.08)	(643.84)
Drought	-0.08	-287.53	-0.20***	-63.69	0.09**	163.46	-0.06	-187.76
	(0.05)	(517.79)	(0.05)	(63.72)	(0.04)	(107.44)	(0.06)	(517.24)
Drought*Post	0.24***	1297.51*	0.35***	163.54*	-0.11	-68.20	0.25***	1392.85*
	(0.09)	(729.03)	(0.08)	(96.13)	(0.08)	(141.67)	(0.08)	(759.20)
HSNP*Drought	-0.03	762.04	0.11	-1.30	0.01	-124.00	0.01	636.74
	(0.08)	(1300.35)	(0.08)	(74.02)	(0.05)	(125.07)	(0.08)	(1302.94)
HSNP*Post*Drought	-0.09	-1,537.51	-0.18	-121.43	0.04	32.99	-0.10	-1,625.95
	(0.11)	(1176.45)	(0.12)	(114.83)	(0.11)	(174.29)	(0.11)	(1193.94)
R-squared		**0.05**		**0.03**		**0.01**		**0.05**

Source: Author's calculation based on HSNP 2010 and 2011 surveys; Robust standard errors (in parentheses) are clustered at the sub-location level; Significance levels *** p<0.01, ** p<0.05, * p<0.1; Marginal effects are evaluated at sample means; quarterly values of private transfers; all estimations include district dummies, household number (OECD scale), household head age (in years), age (in years) squared, indicator of marital status (1=married); gender dummy (1=Male), Drought exposure (1=if household experience drought at baseline, Drought exposure =1 if SPEI index <=-0.84 and zero otherwise); Tropical Livestock Unit (TLU) and logarithm of total monthly per capita consumption expenditure, household wealth (in Kenya Shillings); dependent variable are the likelihood of receiving positive private transfer (Column 1, 3, 5 and 7) and the amount of private transfer received expressed in Kenya Shillings (Column 2, 4, 6 and 8); **N=5,732**.

Table S3.6B: Effects on private transfers received for extreme drought exposure, DID estimates

Variables	Cash transfer		Non-cash transfer		In-kind donation		Total transfer	
	(1=Yes)	KES	(1=Yes)	KES	(1=Yes)	KES	(1=Yes)	KES
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HSNP	0.02	112.72	-0.03	89.46*	0.00	28.34	-0.03	230.52
	(0.04)	(514.58)	(0.04)	(47.20)	(0.04)	(67.79)	(0.04)	(533.35)
Post	-0.07	-199.97	-0.09	39.97	-0.08	-38.12	-0.17***	-198.12
	(0.05)	(397.55)	(0.06)	(46.72)	(0.05)	(88.20)	(0.05)	(416.50)
HSNP*Post	-0.05	-134.32	-0.04	-128.95*	0.02	-20.71	-0.04	-283.98
	(0.07)	(556.78)	(0.08)	(67.79)	(0.06)	(105.66)	(0.07)	(618.63)
Drought	-0.11*	-188.61	-0.18***	-30.66	0.03	129.49	-0.14***	-89.78
	(0.07)	(377.54)	(0.05)	(69.97)	(0.04)	(128.35)	(0.05)	(417.06)
Post*Drought	0.23**	670.32	0.22***	2.45	-0.21**	-189.70	0.25***	483.07
	(0.08)	(491.43)	(0.07)	(114.55)	(0.09)	(135.96)	(0.08)	(607.09)
HSNP*Drought	-0.04	2347.23	0.10	-94.73	0.01	-66.23	0.07	2186.27
	(0.11)	(1871.40)	(0.11)	(75.32)	(0.06)	(160.67)	(0.10)	(1873.28)
HSNP*Post*Drought	0.01	-2,769.85	-0.02	117.19	0.02	98.64	-0.04	-2,554.02
	(0.12)	(1799.83)	(0.14)	(128.86)	(0.10)	(195.54)	(0.13)	(1,827.66)
R-squared		**0.06**		**0.03**		**0.01**		**0.06**

Source: Author's calculation based on HSNP 2010 and 2011 surveys; Robust standard errors (in parentheses) are clustered at the sub-location level; Significance levels *** p<0.01, ** p<0.05, * p<0.1; Marginal effects are evaluated at sample means; quarterly values of private transfers; all estimations include district dummies, household number (OECD scale), household head age (in years), age (in years) squared, indicator of marital status (1=married); gender dummy (1=Male), Drought exposure (1=if household experience drought at baseline, Drought exposure =1 if SPEI index <=-1.50 and zero otherwise); Tropical Livestock Unit (TLU) and logarithm of total monthly per capita consumption expenditure, household wealth (in Kenya Shillings); dependent variable are the likelihood of receiving positive private transfer (Column 1, 3, 5 and 7) and the amount of private transfer received expressed in Kenya Shillings (Column 2, 4, 6 and 8); **N=5,732**.

APPENDIX S3.7.3: EFFECTS ON PRIVATE TRANSFER GIVEN TO OTHER HOUSEHOLDS

Table S3.4.1A: Effects on giving private transfers, DID estimates

Variables	**Cash transfer**		**Non-cash transfer**		**Total transfer**	
	(1=Yes	**KES**	**(1=Yes)**	**KES**	**(1=Yes)**	**KES**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Panel A: Household level effects, N=5,732						
HSNP*Post	0.06	-146.22	-0.05	0.46	0.01	-145.76
	(0.07)	(656.25)	(0.09)	(36.89)	(0.09)	(655.14)
Baseline mean	0.17	442.53	0.23	77.25	0.31	519.78
R-squared		**0.04**		**0.02**		**0.04**
Panel B: Sub-location level effects, N=9,272						
HSNP*Post	0.02	-339.38	-0.04	-66.36	-0.01	-405.74
	(0.06)	(434.73)	(0.09)	(47.02)	(0.09)	(429.49)
Baseline mean	0.20	494.32	0.24	95.30	0.33	589.62
Adjusted R-squared		**0.04**		**0.04**		**0.04**

Source: Author's calculation based on HSNP 2010 and 2011 surveys; Robust standard errors (in parentheses) are clustered at the sub-location level; Significance levels *** p<0.01, ** p<0.05, * p<0.1; Marginal effects are evaluated at sample means; quarterly values of private transfers; all estimations include district dummies, household number (OECD scale), household head age, age squared, indicator of marital status (1=married); gender dummy (1=Male), Drought exposure (1=if households experience drought at baseline), Tropical Livestock Unit (TLU) and logarithm of total monthly per capita consumption expenditure, household wealth (in Kenya Shillings), household head age (in years), household head age (in years) squared; dependent variable are the likelihood of giving other households a positive private transfer (Column 1, 3 and 5) and the amount of private transfer given to other households expressed in Kenya Shillings (Column 2, 4 and 6).

APPENDIX S3.8: EFFECT ON PRIVATE TRANSFER RECEIVED, BY POVERTY STATUS

Table S3.8.1A: Effects on private transfer received by poverty status, DID estimates

Variables	**Cash transfer**		**Non-cash transfer**		**In-kind donations**		**Total transfer**	
	(1=Yes)	**KES**	**(1=Yes)**	**KES**	**(1=Yes)**	**KES**	**(1=Yes)**	**KES**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
HSNP	0.02	1,574.06	0.04	107.76**	-0.01	-9.05	-0.01	1,672.77
	(0.04)	(1,061.40)	(0.05)	(50.49)	(0.04)	(73.63)	(0.05)	(1,053.67)
Post	-0.01	-226.73	0.07	40.13	-0.12**	-133.81*	-0.05	-320.42
	(0.05)	(468.50)	(0.05)	(57.16)	(0.05)	(75.97)	(0.04)	(464.28)
HSNP*Post	-0.03	-1,689.63	-0.07	-119.34*	0.04	42.30	-0.03	-1,766.67
	(0.06)	(1,257.26)	(0.06)	(67.04)	(0.05)	(83.66)	(0.06)	(1,281.45)
Poor	-0.03	-630.68*	0.11**	55.90	-0.02	-34.00	0.03	608.78
	(0.04)	(348.28)	(0.05)	(57.78)	(0.02)	(61.34)	(0.05)	(365.23)
Post*Poor	0.03	192.31	-0.14**	21.66	0.03	69.80	-0.07	283.77
	(0.05)	(389.49)	(0.07)	(67.24)	(0.04)	(129.75)	(0.06)	(472.85)
HSNP*Poor	0.01	-1,463.99	-0.03	-72.97	0.02	13.84	0.02	-1,523.12
	(0.05)	(1,022.85)	(0.07)	(67.06)	(0.03)	(83.61)	(0.06)	(1,002.32)
HSNP*Post*Poor	-0.05	1,501.91	0.01	19.72	-0.05	-64.01	-0.04	1,457.63
	(0.07)	(1,170.47)	(0.09)	(90.32)	(0.05)	(151.44)	(0.08)	(1,216.61)
R-squared		**0.06**		**0.03**		**0.01**		**0.06**

Source: Author's calculation based on HSNP 2010 and 2011 surveys; Robust standard errors (in parentheses) are clustered at the sub-location level; Significance levels *** p<0.01, ** p<0.05, * p<0.1; Marginal effects are evaluated at sample means; quarterly values of private transfers; all estimations include district dummies, household number (OECD scale), household head age (in years), household head age (in years) squared, indicator of marital status (1=married); gender dummy (1=Male), Extremely poor (1=if households is classified as extremely poor at baseline), Tropical Livestock Unit (TLU) and logarithm of total monthly per capita consumption expenditure, household wealth (in Kenya Shillings); dependent variable are the likelihood of receiving positive private transfer (Column 1, 3, 5 and 7) and the amount of private transfer received expressed in Kenya Shillings (Column 2, 4, 6 and 8); **N=5,732.**

Table S3.8.2B: Effects on giving private transfer by poverty status, DID estimates

Variables	Cash transfer		Non-cash transfer		Total transfer	
	(1=Yes)	KES	(1=Yes)	KES	(1=Yes)	KES
	(1)	(2)	(3)	(4)	(5)	(6)
HSNP	0.03	523.04	0.02	-6.35	0.03	516.69
	(0.03)	(943.90)	(0.04)	(20.85)	(0.04)	(942.59)
Post	-0.03	-589.49	0.03	-12.14	-0.02	-601.63
	(0.04)	(528.44)	(0.05)	(17.75)	(0.05)	(526.56)
HSNP*Post	0.05	-486.50	-0.06	-7.93	0.01	-494.43
	(0.06)	(1112.31)	(0.07)	(25.18)	(0.07)	(1104.71)
Poor	-0.03	-232.44	0.02	-22.30	-0.01	-254.74
	(0.03)	(199.08)	(0.05)	(22.74)	(0.06)	(203.83)
Poor*Post	0.00	513.49	-0.08	23.77	-0.04	537.26
	(0.05)	(323.77)	(0.07)	(38.28)	(0.08)	(326.40)
HSNP*Poor	-0.05	-665.51	-0.00	7.75	-0.01	-657.75
	(0.04)	(860.19)	(0.05)	(27.91)	(0.06)	(858.97)
HSNP*Post*Poor	0.02	612.66	0.02	22.71	-0.01	635.37
	(0.07)	(970.83)	(0.09)	(66.16)	(0.10)	(966.22)
R-squared		**0.04**		**0.02**		**0.04**

Source: Author's calculation based on HSNP 2010 and 2011 surveys; Robust standard errors (in parentheses) are clustered at the sub-location level; Significance levels *** p<0.01, ** p<0.05, * p<0.1; Marginal effects are evaluated at sample means; quarterly values of private transfers; all estimations include district dummies, household number (OECD scale), household head age (in years), household head age (in years) squared, indicator of marital status (1=married); gender dummy (1=Male), Extremely poor (1=if households is classified as extremely poor at baseline), Tropical Livestock Unit (TLU) and logarithm of total monthly per capita consumption expenditure, household wealth (in Kenya Shillings); dependent variable are the likelihood of giving out positive private transfer (Column 1, 3 and 5) and the amount of private transfer given to other households expressed in Kenya Shillings (Column 2, 4 and 6**); N=5,732**.

APPENDIX S3.9: MEDIUM TERM EFFECTS OF HSNP ON PRIVATE TRANSFERS

Table S3.9.1A: Effect on private transfer, DID estimates

Variables	Cash transfer		Non-cash transfer		In-kind donations		Total transfer	
	(1=Yes)	KES	(1=Yes)	KES	(1=Yes)	KES	(1=Yes)	KES
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Effect on receiving private transfer								
HSNP*Post	-0.00	-28.31	-0.00	-19.99	-0.10**	-48.97*	-0.01	-97.27
	(0.07)	(128.14)	(0.05)	(13.64)	(0.05)	(25.52)	(0.06)	(130.64)
R-squared		**0.05**		**0.04**		**0.01**		**0.05**
Panel B: Effect on giving private transfer								
HSNP*Post	0.05	-6.11	0.04	5.00			0.04	-1.11
	(0.06)	(109.15)	(0.07)	(7.26)			(0.07)	(104.29)
R-squared		**0.03**		**0.02**				**0.03**

Source: Author's calculation based on HSNP 2010, 2011 and 2011 surveys; Robust standard errors (in parentheses) are clustered at the sub-location level; Significance levels *** p<0.01, ** p<0.05, * p<0.1; Marginal effects are evaluated at sample means; quarterly values of private transfers; all estimations include district dummies, household number (OECD scale), household head age (in years), household head age (in years) squared, indicator of marital status (1=married); gender dummy (1=Male), Tropical Livestock Unit (TLU) and logarithm of total monthly per capita consumption expenditure, household wealth (in Kenya Shillings); dependent variable are the likelihood of giving positive private transfer (Column 1, 3 and 5) and the amount of private transfer given to other households expressed in Kenya Shillings (Column 2, 4 and 6); **N=6,873**.

APPENDIX S3.10: PER SHLLING CROWDING OUT EFFECTS OF PRIVATE TRANSFER RECEIVED

Table S3.10A: Per shlling crowding out effects of private transfer received (using HSNP 2010-2011 sample)

Variables	Cash	Non-cash	In-kind donation	Total private transfer
Panel A: Household level effects, N=5,732				
HSNP*Post	-861.04	-102.40	13.07	-950.36
Deviation in private transfer received (2010-2011)	-727.43	140.71	485.91	-307.46
Per shilling crowding out	$\frac{-861.04}{-727.43} = 1.18$	$\frac{-102.40}{140.71} = -0.73$	$\frac{13.07}{485.91} = 0.03$	$\frac{-950.36}{-307.46} = 3.09$
Panel B: Sub-location level effects, N=9,272				
HSNP*Post	-882.35	-139.75	14.51	-1,007.58
Deviation in private transfer received (2010-2011)	-1,315.45	173.59	12.45	-632.35
Per shilling crowding out	$\frac{-882.35}{-1{,}315.45} = 0.67$	$\frac{-139.75}{173.59} = -0.81$	$\frac{14.51}{531.79} = 0.02$	$\frac{-1{,}007.58}{-632.35} = 1.59$

CHAPTER 4: COMPARING DIRECT AND INDIRECT EFFECTS OF INCOME ON CONSUMPTION OF NUTRIENTS IN KENYA

4.1. Introduction

Malnutrition is a global health problem, especially in developing countries, where it affects over 800 million poor households (IFPRI, 2018). In sub-Saharan Africa (SSA), for instance, the prevalence of malnutrition increased by about 1.5% per annum in absolute terms between 2014 and 2019, affecting approximately 250 million people in 2019 (FAO, IFAD, UNICEF, and WHO, 2020). The prevalence of malnutrition in SSA is estimated to be 8.9% – more than twice the world's average and the highest globally. Consequences of malnutrition include loss of gross domestic product (GDP), an increased risk of chronic diseases among adults, poor pregnancy outcomes, and high child mortality, especially when it interacts with infections like measles, diarrhea, and respiratory disorders (Black et al., 2008; Bailey, West, and Black, 2015; Gakidou et al., 2017).

Given these negative effects of malnutrition, social safety net programs such as Kenya's Hunger Safety Net Program (HSNP) - a cash transfer program - have been proposed to improve nutritional outcomes for poor households.[83] These public programs are intended to reduce poverty and social vulnerability, which are the main drivers of malnutrition (Ruel and Alderman, 2013). However, there is limited empirical evidence on the effects of cash transfers on the consumption of nutrients. And most of the existant research has mainly focused on the effect of social programs on poor beneficiary and non-beneficiary households (i.e., direct effects) and disregarded non-poor, non-beneficiary households (i.e., indirect effects). However, in village economies where risk-sharing practices between communities are strong (see Townsend, 1995; Fafchamps and Lund, 2003; Dercon, et al., 2012), the effects of social programs can also accrue to non-poor, non-beneficiary households through familial or

[83] Other methods of solving malnutrition include food fortification, diet diversification, and micronutrient supplementation. However, these methods can be costly to implement and often do not reach the rural poor in the developing world because they are disconnected from wholesale markets, which are located in urban centres.

community-based channels,[84] and this has a significant effect on the design of policies aimed at reducing extreme poverty and enhancing nutritional uptakes in the rural areas of developing countries.[85] Therefore, understanding both the direct and indirect effects (in terms of income elasticities of nutrient consumption) associated with social safety net programs is key when designing policies aimed at improving household nutrition in rural areas.

To fill this present gap in the literature, the purpose of this paper is to estimate the magnitude of income elasticities (for both HSNP poor beneficiary and non-beneficiary and non-poor, non-beneficiary households) obtained from consumption of nutrients using HSNP dataset collected from Northern Kenya. The HSNP is a Randomized Controlled Trial (RCT) giving an unconditional cash transfer of 2,125 Kenyan shillings (KES) (about US$20) every two months to qualifying households or individuals with the goal of improving, among other things, the food and nutrition security of poor households.[86] The amount was fixed at 75% of the value of food ration provided by the United Nations World Food Programme (which operated in the region in 2006) and is equivalent to about 12% of household baseline consumption expenditure. A unique feature of the HSNP is a contingency benefits plan (or drought emergency fund) for poor beneficiary households in the case of severe drought. In May 2019, 600,000 people were benefiting from HSNP transfers in the 48 sub-locations of northern Kenya.

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[84] For instance, beyond the cash transfers often shared with non-poor, non-beneficiary households, poor beneficiary households also host other family members who cannot afford to self-subsist, thereby increasing household sizes. This reinforces the child-fostering hypothesis, which has been shown to drive food and nutritional consumption at household level. It is, therefore, a common practice for elderly parents (poor beneficiary households) to share a home with their adult children (non-beneficiary households) to ease care, or for richer households (poor beneficiary households) to support the children of less fortunate family members (non-beneficiary households) to enable them to attend distant schools.

[85] In HSNP districts, households share about 23.26% of the transfer they receive (ie., KES 500 out of KES 2,150 received every two months) with neighbours, other family members and friends. The low adoption of unconditional cash transfers (UCT), especially in Africa, can be attributed to social and economic problems such as high poverty rates, recurrent food price hikes, and the prevalence of HIV/AIDS. These challenges have two important implications: 1) they make health, nutrition, and other important outcomes secondary objectives for households; and 2) they affect program design, acceptance, scalability, cost, and impact.

[86] HSNP poor beneficiaries were selected based on three targeting mechanism, either community based targeting, dependency ratio or social pension. Under community based and dependency ratio targeting schemes, households were targeted while under social pension, individual persons were targeted. In this study, we use households to mean those beneficiaries selected through community based and dependency ratio targeting scheme and individuals to mean those selected under social pension schemes.

We use an HSNP 2010–2011 longitudinal sample containing 9,246 poor beneficiary and no-poor, non-beneficiary households in treated and control sub-locations (See appendix 4.1), and exploit the panel nature of our dataset to test whether an intervention intended to reduce poverty and social vulnerability can, at the same time, improve the nutritional status of rural households. Using difference-in-difference specifications, our results revealed that HSNP poor beneficiary households in treated sub-locations significantly increased their consumption of diets rich in vitamin A and C by approximately 96 and 51 percent, respectively as a result of participating in HSNP compared to those in control sub-locations. Moreover, HSNP poor beneficiary households in treated sub-locations almost doubled consumption of foods rich in vitamin A (like cheese, eggs, oily fish, milk and fortified low fat spreads) - which are sourced from animals. At the same time, we show that HSNP poor beneficiary increase consumption of beta carotene rich diets by 61 percent compared to households in control sub-locations. These results are statistically significant at conventional levels. Another important trend is that HSNP non-poor, non-beneficiary households in treated sub-locations increased their intake of vitamins A by 69 percent compared to those in control sub-locations. We rule out alternative pathways that households might have used to increase their consumption, such as increased earnings, savings, investments, and price increases of goods. We conclude that the rise in nutrition was primarily the result of sharing the HSNP transfers among social network members. Finally, we evaluate the robustness of our results under several extensions. These cover situations when (a) households experience natural calamities (i.e drought), (b) crop production cycles and (c) HSNP targeting types, where the transfers are given to females, are considered.

Our paper makes three important contributions to the economic literature. First, we contribute to the discussion on nutrient-income elasticity[87] from a developing country perspective, where research is still limited. In Kenya, for instance, Dietrich and Schmerzeck (2020) found that changes in income did not affect available nutrients, while Haushofer and Shapiro (2018) found that income had a positive effect on protein consumption. At the international level, some

[87] Income elasticity is the percentage change in consumption of nutrients as a result of a 1% change in income. This elasticity is important in understanding the determinant of nutrition and whether the social safety net is effective in promoting higher nutrition in poor households.

studies have found a positive effect of income on nutrient intake (see Leroy et al., 2010 [for Mexico]; Jha, Bhattacharyya, and Gaiha, 2011 [for India]) while others have found little or no effect of income on nutrient deficiencies (Gertler, 2004 [for Mexico]; Caldés, Coady, and Maluccio, 2006 [for Mexico, Honduras, and Nicaragua]). Our result complements these previous studies' findings by showing that HSNP non-poor, non-beneficiary households also increase their nutritional intake, when public transfers are allocated to poor beneficiary households only. This allows us to identify the potential spillover effects associated with the implementation of HSNP policies on non-poor, non-beneficiary households.

Second, our study adds to the literature on the effectiveness of government aid (in the form of cash transfer) in improving household nutrition. Here, Hoddinott, and Skoufias (2004) showed that transfers helped households increase their consumption of fruits, vegetables, and animal products. In addition, Angelucci and De Giorgi (2009) showed that beneficiary households increased their food consumption by almost 10% compared to those in control sub-locations. Our results complement these previous findings in two ways. First, we document that these positive effects of transfers received on nutrient consumption persist, even in a presence of drought, through existing risk-sharing mechanisms within rural communities of Kenya. Second, we show that these positive effects of income are more pronounced when households source their nutrients primarily from local food markets rather than through self-production, signifying the important role these markets play in the nutrition of poor households. Finally, our study extends the discussion on consumption smoothing in low-income countries. It is often argued that poor households tend to consume processed foods and beverages, which are generally not rich in calories (Subramanian and Deaton, 1996). Here also, we show that HSNP poor beneficiary households in treated sub-locations shift their consumption to diets rich in heme iron and vitamins compared to those in control sub-locations.

The remainder of the paper is organized as follows. Section 2 provides a summary of the experimental setup and the data sources, whereas section 3 discusses the outcome variable: nutrition. The estimation strategy is detailed in section 4. The results are discussed in section 5. Section 6 investigates the results under various scenarios. The last section 7 concludes the paper.

4.2. Experimental design and data sources

We use a randomized controlled trial (RCT) dataset from the Hunger Safety Net Program (HSNP) collected by Oxford Policy Management in collaboration with other stakeholders.[88] The HSNP is an unconditional cash transfer program aimed at improving the food and nutritional security of poor households in northern Kenya, among other objectives. The program is ongoing and is currently benefiting 97,967 households (approximately 600,000 people) with a budget of KES 0.54 billion in May 2019.[89] The transfer is delivered in two tranches: a regular transfer and a drought emergency fund. Specifically, every beneficiary household or individual was entitled (at baseline) to about KES 2,150 (US$ 20)[90] every two months. This amount corresponds to about 12% of the average household consumption expenditure in 2009 or approximately 75% of the food ration of the World Food Programme in 2006.[91] The drought emergency fund (or contingency benefit plan) is a form of risk insurance that pays out about 75% of the HSNP cash transfer amount received by beneficiary households in the case of a severe drought. Situations of drought are determined by the Normalized Difference Vegetation Index (NDVI) of every HSNP district (Merttens et al., 2013).

The HSNP covered four arid and semi-arid districts: namely Turkana, Mandera, Marsabit, and Wajir.[92] These districts are characterized by high levels of poverty with over 85% of residents living below the poverty line in 2005/06 (KNBS, 2019). Crop yields are low and the application of improved technologies to enhance yields is limited. The region is characterized by frequent

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88 These stakeholders include the Government of Kenya through the Ministry of Devolution and Arid and Semi-Arid Lands; the National Drought Management Authority of Kenya; the UK's Department for International Development (DFID); Equity Bank, Kenya; the International Development Association of the World Bank; the National Registration of Person's Bureau; the county governments of Wajir, Mandera, Turkana and Marsabit; the Ministry of Interior and Coordination of National Government; and the Ministry of Labour and Social Protection of Kenya.

89 See www.hsnp.or.ke for up-to-date information.

90 This amount was increased in September/October 2011 to KES 3,000 and to KES 3,500 in March/April 2012. In March/April 2011, the HSNP contingency fund made a once-off double the transfer payout to HSNP beneficiary households as a result of a severe drought.

91 The WFP food ration is relief-based food assistance provided as a protection ratio for hunger-stricken households. The program operated in the Marsabit, Mandera, Turkana and Wajir districts of Kenya until 2006. It benefited over 425,000 households (women and children) by giving out cash entitlement of about KES 4,000 (US$39) every three months. This WFP transfer provides about 65% relief on food equivalent, based on local prices.

92 Source: https://microdata.worldbank.org/index.php/catalog/1915/related-materials.

droughts, which cause about 20% harvest losses. Moreover, the region suffers from communal conflicts over water and grazing land, and poor maternal and child health; cases of severe underweight, stunting, and wasting are almost double the national average (see Figure 3). Amongst the four HSNP districts, Mandera had the highest incidence of stunting (HAZ of 47.6 standard deviation), while Wajir has the lowest incidence (HAZ of 24.7 standard deviation) (KEBS, 2015). This can be attributed to two reasons. First is the nomadic lifestyle of households in the district. According to Mertens et al., (2013), the Mandera district has the highest number of pastoralists compared to other HSNP districts. Secondly, HSNP districts were severely impacted by two covariate shocks (i.e., drought and inflation) than other districts in Kenya which magnified the incidence of malnutrition.

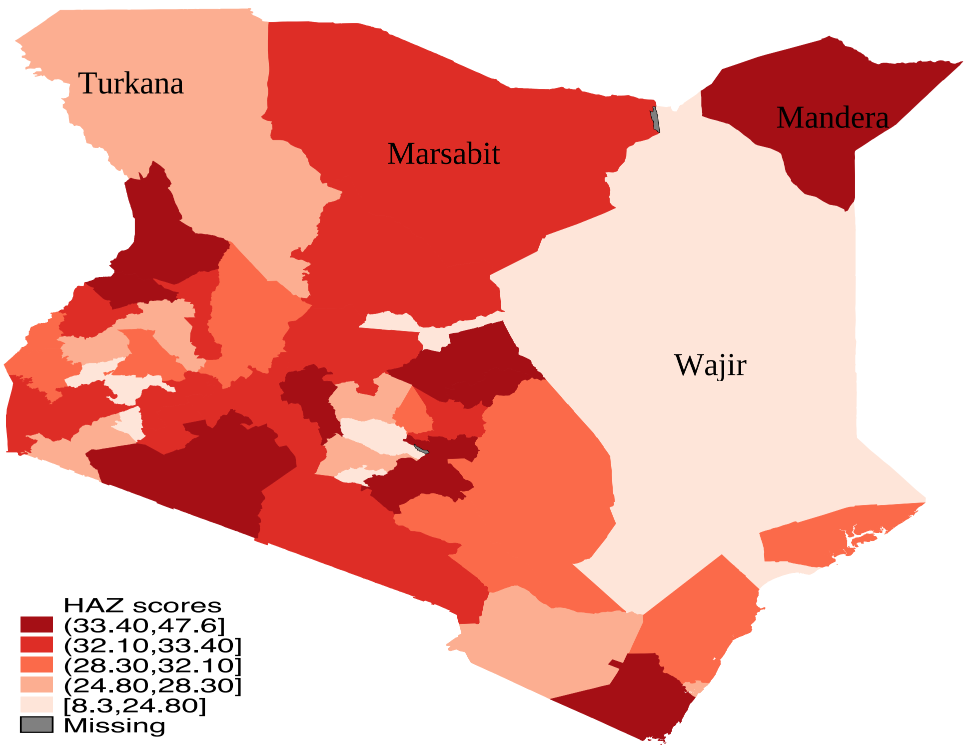

Figure 3: Height for age Z (HAZ) scores

Source: Constructed by the authors based on data collected from KEBS (2015)

The design of HSNP is simple: it is made up of one treatment and control arms only. A treatment sub-location is one selected to receive transfers, while control sub-location did not receive transfers until December 2012. Households in the control sub-locations were also not told whether they would receive transfers in the future to prevent priming effects. Across the HSNP districts, 48 sub-locations (12 in each district) were randomly selected for inclusion in the program.[93] And because of a geographical phase-in, 24 sub-locations were randomized out and did not receive the treatment between 2010 and 2012. The randomly selected sub-locations were matched in pairs with the treated sub-locations based on population densities.

Household targeting involved three mechanisms: either community-based, dependency ratio or social pension. The selection process of households into either treatment or control sub-locations followed a similar pattern to ensure comparability. In community-based targeting (CBT), local leaders selected households, which they deemed poor, to receive the transfer. These comprise about 50% of all households under this mechanism. Under the dependency ratio targeting (DRT), a household was selected if a percentage of its members, younger than 18 years or older than 55 years, exceeded a threshold set by the project. Under the social pension targeting, equal numbers of men and women benefited from the program, but women were the majority recipients in the CBT (81.9%) and the DRT (73.7%).

Similar to the sub-locations, the program rollout and data collection followed a staggered approach. This means that sub-locations were introduced on a month-by-month basis over 12 months to account for seasonal differences.[94] At baseline, one sub-location in each pair (either treatment or control) was selected through a public lottery attended by community leaders and HSNP officials. After selection, data collection started before any household received their first HSNP transfer. This staggered procedure was followed in other survey rounds. It is important to highlight that once a household started to receive the transfer, no other household was allowed to join the program until December 2012. This enables us to estimate the impact of the HSNP on nutrient consumption.

HSNP poor beneficiary households were selected from a list obtained from administrative records. In each sub-location, 66 households were selected using a simple, random sampling

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[93] A sub-location is the smallest administrative unit, comprising about 200 households living close to each other and is headed by a chief, assisted by local leaders.
[94] A treated sub-location is one selected to receive the HSNP transfer immediately after the baseline survey, while a control sub-location is one that did not receive any HSNP transfer until the end of the first phase (2010–2012) of the program.

procedure from a sampling frame containing HSNP poor beneficiary households (See Appendix 4.1). If there was no response, a replacement household was drawn randomly from the list of the remaining households on the administrative record until the required sample was reached. For HSNP non-poor, non-beneficiary households, listing was undertaken in a sample of three settlements (either main, permanent or non-permanent) available within each sub-location. In total about 44 HSNP non-beneficiaries were sampled in each sub-location. In case of non-response, HSNP non-poor, non-beneficiary households were sampled using a replacement list stratified by residency status (either resident or non-resident) and settlement type. In both treated and control arms, information was collected from poor (i.e., HSNP poor beneficiary) and non-poor (i.e., HSNP non-poor, non-beneficiary) households (See Appendix 4.1 for details).

The information was collected using a detailed questionnaire. In the HSNP sample, the attrition rate was low. For instance, between 2010 and 2011, the attrition rate averaged about 8%. At the household level, the average attrition rate was about 4.4% between the 2010 and 2011 HSNP samples. Across the four districts, Mandera and Wajir had the highest attrition rates, partly because of the nomadic nature of most households (Merttens et al., 2013). The low attrition rate meant that our results are unlikely to have been impacted by attrition bias. Our final sample is HSNP 2010–2011 comprising 9,246 households (5,722 poor beneficiary and 3,524 non-poor, non-beneficiary households, See appendix 4.1 for details). We used this sample because we had detailed information on the HSNP non-poor, non-beneficiary and poor beneficiary households.

4.3. Measuring nutrition

In measuring household nutrition, we adopted a food consumption-based approach due to data availability.[95] We use household food consumption data collected in 2010 and 2011 to calculate nutritional indicators. The HSNP survey instrument contained detailed information on 54 food items collected on a seven-day recall period. We differentiated between food items that are self-produced, purchased from local markets, and received as gifts. Other important

[95] Other commonly applied methods for measuring household nutrition are clinical and anthropometric measures (De Haen, Klasen, and Qaim, 2011).

information included the quantity of each food item consumed, per unit costs (for market-sourced foods), and total expenditure incurred by each household.

In estimating the amount of nutrients consumed in a food item, we followed a flexible approach involving four main steps (Shapiro, Haushofer, and Almås, 2019). First, we converted all reported quantities of foods into a single unit (in this case grams) to be consistent with the food consumption tables of Kenya.[96] In doing so, we made assumptions about the local names and assigned weights of food items consumed by households but not available in Kenya's food consumption table.[97] In the second step, we converted these weekly amounts of food consumed into 100 grams, by taking into account edible portions of these food items.[98] In doing so, we followed the Food and Agriculture Organization's (FAO's) guidelines on food matching and applied Kenya's food consumption tables 2018[99] (Stadlmayr et al., 2012; FAO/Government of Kenya, 2018). In the third step, we aggregated the amount of each nutrient consumed at the household level. In the final step, we standardized the amounts of nutrients consumed by household size, per adult equivalent (based on the OECD modified scale), to facilitate comparison with previous studies.[100] We used these standardized amounts of nutrients

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[96] Food consumption table for Kenya is available at: https://www.google.co.za/url?sa=t&rct=j&q=&esrc=s&source=web&cd=&cad=rja&uact=8&ved=2ahUKEwjFp_2dnartAhU6UhUIHb-LDgcQFjAAegQIAhAC&url=http%3A%2F%2Fwww.fao.org%2F3%2FI8897EN%2Fi8897en.pdf&usg=AOvVaw2eLZv_9jRaK9xn6KO_OnEh

[97] For instance, we assumed that 1 debe of maize grain is equivalent to 1 kilogram; 1 pachaka/tenga equals 500 grams of vegetables; 1 mango equals 150 grams; 1 head and 1 handful of milk powder equals 220 and 110 grams, respectively. In instances where households reported the unit of measurement of bread as 25 kilograms, we assumed this is equal to 700 grams as this is the most common bread type in most Kenyan households; Changes in these assumptions will not affect the reliability of our results. We double checked these assumptions by conducting an online interview with key experts working in the nutrition field in Kenya and across Africa.

[98] We use the word nutrient available or consumed interchangeably. It is important to recognize that households reported only the quantities of foods available in the previous seven days without highlighting whether these foods were consumed or not, and in which form they were consumed. In all instances, for the sake of simplicity, we assumed that all nutrients available in foods were consumed and we used the raw form of these foods. This assumption reflects the socio-economic realities of the households in rural Kenya; the lack of food storage facilities combined with a high level of food vulnerability makes it difficult to assume a situation where foods can be stored for a long time.

[99] The Kenyan food consumption tables did not classify chat/miraa and tobacco products as foods. So, we gave them zero nutrient values because they are not consumed but either smoked or chewed and then spat out.

[100] This scale assigns 1 to a household head, 0.5 to an additional adult and 0.3 to every child in the household. For instance, a household of three people (head, spouse, child) will have a score of 1.8 (Hagenaars, De Vos, and Zaidi, 1994).

consumed per adult as outcome variables. We provide a brief overview of nutrients consumed per adult equivalent in Table 17. These nutrients were selected based on their importance for body growth (Subramanian and Deaton, 1996).

One can observe, at a glance, that the HSNP (poor beneficiary and non-poor, non-beneficiary) households in treated sub-locations increased their consumption of diets rich in nutrients compared to those in control sub-locations, who consumed more cereals, as evidenced by high levels of nutrients per adult equivalent (see Table 17 and Appendix 4.1 for descriptive statistics and definition of HSNP poor beneficiary and non-poor, non-beneficiary households, respectively). In rural villages, where agriculture is the mainstay of most households, cereal-based diets are cheap and, therefore, contribute a significant portion of the household caloric share. As a result, we did not exclude any household based on the amount of nutrients consumed, contrary to previous studies (i.e Dietrich and Schmerzeck, 2020) which excluded households with energy consumption below a given threshold . Instead, we applied a logarithm to the consumed nutrients and vitamins per adult equivalent to minimize the influence of outliers and preserve the balanced nature of our sample.[101]

Table 17: Descriptive statistics of outcome variables at baseline using student t-test estimation procedure

Outcome variables	**HSNP poor beneficiary households**		**HSNP non-poor, non-beneficiary households**	
	Full sample mean (SD) (1)	**Control-Treated households (p-value) (2)**	**Full sample mean (SD) (3)**	**Control-Treated households (p-value) (4)**
Nutrients consumed per adult equivalent				
Energy (Kcal)	17,440.55	353.81	20,445.14	428.78
	(19,670.81)	(0.63)	(18,041.66)	(0.62)
Protein (g)	575.84	0.52	655.26	61.92
	(1,207.43)	(0.99)	(984.50)	(0.19)
Fat (g)	336.55	3.37	424.28	3.86
	(441.10)	(0.84)	(638.03)	(0.90)

[101] We applied sine hyperbolic transformation every time we mention logarithm (Bellemare & Wichman, 2020). The advantage of this method is that it preserves zero values tha would have otherwise been recorded as missing in the case of the traditional natural logarithm.

Fibre (g)	356.16	8.40	385.617	-3.40
	(521.07)	(0.67)	(438.877)	(0.87)
Carbohydrate(g)	2,825.49	73.95	3,285.24	41.4
	(3,217.27)	(0.54)	(2,912.03)	(0.77)
Zinc (mg)	88.61	1.74	99.89	5.07
	(109.20)	(0.67)	(94.79)	(0.26)
Calcium (mg)	4,308.61	22.49	5,383.35	883.40
	(9,227.17)	(0.95)	(8,615.91)	(0.03)**
Iron (mg)	139.22	–3.51	158.27	–3.37
	(161.77)	(0.56)	(153.19)	(0.64)
Heme iron (mg)	26.03	–2.51	29.97	5.95
	(72.08)	(0.35)	(75.38)	(0.10)
Vitamin A (mcg RAE)	758.86	33.22	1056.68	70.32
	(786.28)	(0.26)	(1,096.11)	(0.18)
Vitamin B_{12} (mcg)	17.24	1.81	22.90	6.61
	(28.29)	(0.09)*	(37.62)	(0.00)***
Vitamin C (mg)	121.41	–45.45	181.55	–68.97
	(300.68)	(0.00)***	(479.39)	(0.00)**
Food folate (mcg)	15.01	0.89	14.59	1.09
	(4.49)	(0.00)***	(4.61)	(0.00)***
Riboflavin (mg)	68.14	–25.21	75.18	–13.77
	(614.41)	(0.27)	(472.63)	(0.54)
Beta carotene (mcg)	1,467.83	–641.72	2,168.51	–831.76
	(3,280.10)	(0.00)***	(5,767.37)	(0.00)**
Observations	**2,861**	**2,861**	**1,762**	**1,762**

Notes: Standard deviation (SD) are in parentheses (for column 1 and 3); *, ** and *** significant at 10%, 5% and 1% levels, respectively. Kcal is kilocalories; RAE is retinol per adult equivalence. All nutritional variables are weekly per adult equivalent. Control-Treated households captures the differences in means between HSNP (poor beneficiary and non-poor, non-beneficiary) households in control and treated sub-locations; Control-Treated households refers to the difference between HSNP poor beneficiary (i.e., A verse B households) and non-poor, non-beneficiaries (i.e., C verses D households) in control and treated sub-locations; p-value captures the level of significance between HSNP poor beneficiary and non-poor, non-beneficiary households in treated and control sub-locations.

Another striking pattern is the high median compared to mean values for all nutrients consumed by both HSNP poor beneficiary and non-poor, non-beneficiary households. This difference is observed across all nutrients except for heme iron and riboflavin. This supports the symmetrical nature of the sample. Moreover, another important pattern relates to the high percentage of heme iron[102] in the diets of poor, HSNP households. In general, rich households (those in the top 25% of per capita consumption expenditure (PCE) consumed about 366% (or five times) more than those in the lowest 25% of PCE (See Table 11A, in appendix 4.2). Here, our observations are similar to those of Skoufias, et al., (2009) who showed that households in the top 25% of PCE consumed about 6.5 times more heme iron than those in the lowest 25% PCE in Tanzania. However, we find a significant difference between the PCE of the top and bottom 25th percentile households in the consumption of foods rich in vitamins C, B_{12}, and riboflavin at about 197%, 69%, and 64%, respectively (See Table 11A, in appendix 4.2).[103] These results bring two important facts to bear. First, a household's nutrient consumption tends to follow the availability of resources. This seems to support the notion that malnutrition is a result of poverty and, therefore, implementing social safety net programs could reduce malnutrition. Second, we find that resource-rich households are able to meet their nutritional requirement whereas resource-constrained households are not. This means that for the resource-poor households, food is a necessity, while for resource-rich households, food is a luxury.

4.4. Covariate balancing test of control variables

We report descriptive statistics and covariate balancing tests of the HSNP households (see Table 18 and Appendix 4.1). Our aim here was to assess the effectiveness of the randomization procedure in producing comparable groups from treatment and control sub-locations. In undertaking covariate balancing tests, we focused our analysis on the 2,861 poor beneficiary and 1,762 non-poor, non-beneficiary households interviewed in 2010 (i.e., baseline data for the HSNP households in our balanced panel). These households were reinterviewed in 2011, which allowed us to form a balanced panel sample for our final results. One message (from Table 18, i.e., baseline data) is that the HSNP poor beneficiary samples are comparable in terms of covariates for about 50 percent of control variables used in our analysis. Specifically, we

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[102] Heme iron is sourced from blood and muscle tissues. It is rich in proteins, mainly found in animal products such as fish and poultry, and it is easily absorbed by the body.
[103] We calculated these figures by dividing the interquartile range with the figures found under the bottom 25 of consumption. For instance, energy (Kcal) = 0.615/10.003 = 0.0615. We follow this formula for all the outcome variables in Table 17.

observed a statistically significant difference in Tropical Livestock Unit (TLU)[104], household size, productive asset ownership, and household participation in formal employment. To minimize possibility of randomization bias, we rely on DID estimators in evaluating treatment effects. Moreover, we control for baseline differences in all regressions. In the HSNP non-poor, non-beneficiary households, only the household size, the age of the household head and employment participation are not comparable at baseline. This provided support for our empirical estimation that we were dealing with unblocked RCT dataset and that these groups of households are comparable. In addition, they provided suggestive evidence of the effectiveness of the HSNP randomization in reaching rural, poor households as evidenced by higher mean values (Column 2 and 4) amongst HSNP poor beneficiary households in treated and control sub-locations[105].

Table 18: Covariate balance tests at baseline using student t-test estimation procedure

Variables	**HSNP poor beneficiary households**		**HSNP non-poor, non-beneficiary households**	
	Full sample mean (SD)	**Control-treated households (P-value)**	**Full sample mean (SD)**	**Control-treated households (P-value)**
Tropical Livestock Unit (TLU)	7.59 (17.14)	–1.06 (0.10)*	9.21 (14.81)	–0.43 (0.55)
Household size AE	4.51 (1.76)	–0.29 (0.00)***	3.99 (1.77)	–0.24 (0.00)***
Gender of head (1=Male)	0.68 (0.46)	–0.02 (0.31)	0.81 (0.39)	0.01 (0.69)
Age of head (years)	52.58 (15.64)	0.18 (0.76)	42.73 (14.03)	–1.27 (0.06)*
Marital status of head (1=Married)	0.68 (0.46)	–0.00 (0.80)	0.82 (0.38)	0.01 (0.44)
Employment participation (1=Yes)	0.10 (0.29)	–0.04 (0.00)***	0.08 (0.27)	–0.05 (0.00)***

[104] TLU is an index used to aggregate different livestock types into one single indicator to facilitate international comparison (Jahneke, 1982). Typically, 1TLU is taken to be equivalent to 1 cattle, 0.1 of either a goat,sheep,donkey, ass or mule, 1.4 of camel and 0.01 of a poultry

[105] As noted in Barrett and Carter (2010), the randomization bias common in small samples is not a problem in our dataset.

Economic activity of head (1=Agriculture)	0.45 (0.50)	0.00 (0.99)	0.44 (0.50)	0.01 (0.79)
Own production assets (1=Yes)	0.20 (0.40)	–0.03 (0.09)*	0.22 (0.42)	–0.06 (0.00)***
Observations	**2,861**		**1,762**	

Notes: Production assets include a water drum, animal cart, oxen plough, wheelbarrow, sickle, pick axe, fishing net, panga, and spade; ***, **, and *** correspond to 1%, 5% and 10% significance level, respectively, SD is the standard deviation; Control-Treated households refers to the mean difference between HSNP poor beneficiary (i.e., A verses B) households and non-poor, non-beneficiaries (i.e., C verses D) households in control and treated sub-locations; p-value captures the level of significance between the mean difference between HSNP poor beneficiary households and non-poor, non-beneficiary households in treated and control sub-locations.
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Another important observation is that HSNP households are income poor and they depend mainly on rainfed agriculture for livelihood. This implies that they do not benefit from the growing market of animal-sourced proteins. On average, households keep about eight TLUs (or 1.68 TLUs per household member) which translates into about eight beef cattle or six camels (See Jahneke, 1982). Therefore, they are unable to derive any surplus from selling eight beef cattle or six camels in the market. This figure of eight TLUs is below the recommended minimum of 15 TLUs necessary for a household to produce new stock in presence of drought. The high proportion of poor households in the HSNP sample is not surprising as this program was pro-poor. Finally, household heads were male, married, outside of the productive age group (i.e., 15–49 years), and with few members participating in employment activities that provided either food or cash grants.

4.5. Estimation strategy

We estimate the effect of the HSNP on a host of outcomes grouped into nutrients. For each of the outcomes, we estimate Equation 3.1 with and without explanatory variables. However, only results where baseline covariates are included are presented.

The model we estimate is specified as follows:

$$Y_{is} = \beta_0 + \beta_1 HSNP_i + \beta_2 X_i + \varepsilon_{is} \ldots\ldots\ldots (3.1)$$

Where Y_{is} is the outcome variable of interest (in this case, a log of the weekly amount of nutrients consumed by households per adult equivalent) for a given household i residing in sub-location s; $HSNP$ is the participation dummy which equals one if a household lives in a sub-location selected to receive the transfer and zero otherwise; X_i are covariates shown in Table 18 which includes HSNP which equals one if a household resides in a sub-location selected to start receiving the transfer and zero otherwise, household size per adult equivalent, ownership of a production asset (dummy), gender of a household head (dummy), age and age squared (in years) of a household head, marital status of household head (dummy), household head main economic activity (dummy), any member of the household participating in an employment program giving food or cash for work (dummy), district dummies with Turkana as the base district. Finally, ε_{is} is the white noise. In estimating the model, we cluster standard errors at the sub-location level and apply household weights to control for sample attrition.[106] We estimate Equation 3.1 by using an Ordinary Least Squares (OLS) regression on a cross-sectional dataset- i.e., HSNP 2011 sample only.[107] The impact of the HSNP is captured by coefficients on β_1.

Although the OLS result provides a picture of how participation in the HSNP influences the consumption of nutrients, vitamins, and minerals, it does not account for possible unobserved heterogeneity. In addition, it fails to account for the non-zero outcomes observed at a baseline. This means that results generated from the OLS estimations can be thought of as similar to an intention to treat effects but estimated at a cross-sectional level. To correct for these weaknesses, we benefit from the randomization and panel nature of the HSNP dataset to estimate a difference-in-difference (DID) approach.

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[106] A household weight is the inverse probability of being selected by strata. For HSNP poor beneficiary households (i.e., group A and B, see Appendix 4.1), household weights were calculated as; $W_i = \frac{N_i}{n_i}$ where; n_i denotes the number of HSNP households interviewed in a given sub-location i while N_i captures the number of beneficiaries listed in the HSNP administrative data for a given sub-location i. For non-poor, non-beneficiary households (i.e., group C and D, see Appendix 4.1), household weights were calculated as; $W_i = \frac{1}{[\frac{a_{ijk}}{A_{ijk}} * \frac{1}{b_{ij}} * \frac{1}{C_{ij}}]}$ where; A_{ijk} is the total number of non-beneficiary households residing in k in the selected settlement j and sub-location i; a_{ijk} is the umber of households residing in k in settlement j and sub-location i that were interviewed; b_{ij} is the total number of segments in settlement j and sub-location i (with $b_{ij} = 1$). Finaly, C_{ij} captures total number of settlement of type j in sub-location i. These weights were provided in the dataset (see Merttens et al., 2013).

[107] We estimated OLS regression using the HSNP 2011 survey only with and without covariates for poor beneficiary and non-poor, non-beneficiary households separately. However, we present only regressions in which covariates are included in the model.

4.5.1. Difference-in-Difference approach

When estimating a DID specification, one needs to define who the beneficiaries are in a study. One way of defining a beneficiary is to assume that all households residing in a sub-location selected to participate in the treatment (in this case the HSNP transfer) actually received the transfer, while those in the control sub-locations did not receive this treatment until the program conclusion. In this case, the impact of an intervention can be obtained simply by comparing the households in the sub-locations selected to receive the treatment with those in control sub-locations based on a given outcome of interest. The results from such analysis are commonly referred to as intention-to-treat (ITT) or average intention-to-treat (AITT) effects. This is because they compare only the outcome variables between households in treated sub-locations with those in control sub-locations based on eligibility, but not on actual and effective program participation. The identification assumption is that any change in the outcome variable would have been the same for poor beneficiary households in control and treated sub-locations had there not been an intervention (Moffitt, 2001).[108]

Under an ITT effect, we estimate the following equation:

$$Y_{ist} = \beta_0 + \beta_1 HSNP_s + \beta_2 Post_t + \beta_3 (HSNP_s * Post_t) + \beta_4 X_{it} + \varepsilon_{ist} \ldots\ldots \text{ (3.2)}$$

Where Y_{ist} is the outcome variable for a household i living in sub-location s in year t. $HSNP_s$ is an indicator variable, which equals one if a household resides in a sub-location s in year t, which was selected to receive the HSNP transfer and zero otherwise. $Post_t$ is a year dummy taking a value of one for a follow-up survey (i.e., if data collection happened in 2011) and zero otherwise. X_{it} captures household and community-level characteristics which includes HSNP which equals one if a household resides in a sub-location selected to start receiving the transfer and zero otherwise, household size per adult equivalent, ownership of a production asset (dummy), gender of a household head (dummy), age and age squared (in years) of a household head, marital status of household head (dummy), household head main economic activity

[108] We do not present parallel trends analysis (in graphical form) because we only have one follow up period, i.e., HSNP 2011 survey only. Given that the program had just operated for one year, not much difference can be observed within our dataset.

(dummy), any member of the household participating in an employment program giving food or cash for work (dummy), district dummies with Turkana as the base district. Finally, ε_{ist} is the mean zero and the constant variance error term. In Equation 3.2 the estimated β_3 is the ITT effect and it captures the difference in the HSNP program participation between HSNP poor beneficiary households in treated sub-locations versus those in control sub-locations. We estimate this model for every outcome variable (in Table 17) by using the HSNP 2010–2011 panel sample.

There are two benefits associated with the estimation of ITT effect. First, it helps to overcome possible selection bias in the absence of a perfect balance in baseline characteristics. Second, the estimator accounts for time-invariant heterogeneity and non-zero outcome variables at the baseline level (Greene, 2012; Pamuk et al., 2015). Despite the above merits, however, ITT estimates may be misleading in the absence of full compliance. This is because the ITT effect estimates do not account for possible non-compliance in program participation, which is a common problem encountered in many least developing countries (Angrist, 2006). For instance, in the HSNP 2011 survey, about 3% of HSNP beneficiary households in sub-locations selected to receive the transfer did not actually receive the transfer.[109] Even among those who reported having received the transfer, there are variations in the number of months they reported having received the transfer. In the dataset, we find that median HSNP poor beneficiary households received on average five transfers instead of the possible six transfers in the 2011 survey.

The reason for not receiving the transfer was exogenous to beneficiaries, so the estimate of the ITT effect is likely to be contaminated by errors arising from operational challenges, which are outside of the control of beneficiaries. The estimates are, therefore, biased downwards, given that the conditional mean of the outcome variable among HSNP poor beneficiary beneficiaries would be calculated inclusive of those households that did not benefit or only partially benefited from the program. However, despite these limitations, the ITT effect is still important

[109] About 33 out of the 1,431 HSNP poor beneficiary households in sub-locations selected to start receiving the transfer did not receive the transfer (or 33/1,431=2.3%) due to a technical hitch in registration. This means that about 2.3% of households who were supposed to receive the HSNP transfers did not actually receive their full amounts in the 2011 survey.

to policymakers in that it provides a first-hand overview of what the impact of a given program would look like in the absence of full compliance. In light of the above argument, we first estimate the ITT effects and present our results alongside the estimates drawn from local average treatment effects.

4.5.2. Estimating the local average treatment effects

The best way of capturing non-compliance problems is to estimate the treatment-on-the-treated (ToT) effects, also known as the local average treatment effects. As the HSNP households did not meet full compliance (as discussed earlier), in addition to the ITT effect, we estimated ToT effects limiting our analysis to the HSNP poor beneficiary households sample only. Hence, our aim was to examine whether actual receipt of the HSNP transfer would impact, in a different way, the outcome variables for households who reported having received the positive transfer amounts or the number of times they received the transfer.

We estimate ToT effect using the following equation:

$$Y_{ist} = \beta_0 + \beta_1 HSNP\_Transfer_s + \beta_2 Post_t + \beta_3 (HSNP\_Transfer_s * Post_t) + \beta_4 X_{it} + \varepsilon_{ist} \ldots\ldots (3.3)$$

Where $HSNP\_Transfer_s$ is the participation variable. We capture participation in two ways. First, we estimate the model using a continuous variable calculated as a ratio of the number of times (in months) a household is reported having received HSNP transfer relative to the maximum number of times (in months) households reported having received the transfer in a given sub-location. We refer to this ratio as the HSNP intensity index and it takes the values between zero and one. Second, we also capture actual participation as a dummy variable, which equals 1 if a household reported a positive value in the number of times they had received the HSNP transfer and zero otherwise. All other remaining variables are as described in Equation 3.2. Finally, we cluster the standard errors at the sub-location level and applied household weights, as provided in the dataset, to account for sample attrition.

There are two important conditions that must be met in estimating the ToT effects. First, the offer to participate in the program needs to be random and this means that households in control sub-locations should be an appropriate comparison group to those in treated sub-locations. This condition is met in our data (for HSNP poor beneficiary households), given the fact that the introduction of sub-locations into the program was random and selection was done at a public lottery, which was attended by program officials and community leaders. A second condition that may bias result from ToT effect regression is when receipt of HSNP transfer is defined by household behaviour or choices made by a household head or other responsible member. However, given that the HSNP poor beneficiary households in treated sub-locations were left out (for those who experience technical challenges with mobile SIM registration) for reasons beyond their control, this was no longer a concern in this program.

4.6. Results and discussion

We organize our results and discussions based on the outcome variable: consumption of nutrients, and by the model estimated. We first provide a brief discussion of an OLS regression for the HSNP poor beneficiary and HSNP non-poor, non-beneficiary households separately (Table 19). We extend this cross-sectional result to a panel framework using the HSNP 2010–2011 sample covering 5,722 poor beneficiary households (Tables 20 and 21, columns 2, 3, and 4). We compare our result with 3,524 HSNP non-poor, non-beneficiary households interviewed in the 2010 and 2011 survey periods (Tables 20 and 21, column 5).

4.6.1. Impact of the HSNP on household nutrient consumption

We report Ordinary Least Squares (OLS) estimates for each nutrient consumed by households separately by eligibility criteria (either HSNP poor beneficiary or HSNP non-poor, non-beneficiary). One emerging pattern (in Table 19, column 2) is that, for HSNP poor beneficiary households, estimates are positive and statistically significant (at conventional levels, $P<0.1$) for nutreients and vitamins, except for heme iron and Vitamin B_{12}, suggesting that the HSNP had a high impact on vitamins and nutrient consumption. Specifically, we find that receipt of HSNP transfer for HSNP non-poor and poor beneficiary households in treated sub-locations significantly increased consumption of non-heme iron by approximately 16 and 17 percentage points compared to those in control sub-locations, respectively. At the same time, we observe an increase of 10 and 21 percentage points in the consumption of diets rich in Carbohydrates and Calcium, respectively for HSNP poor beneficiary households compared to those in the control sub-locations. These results are statistically significant at conventional levels. In general, we observe HSNP beneficiary households in treated sub-locations to consume more of micro-nutrients and vitamins rich diets compared to those in control sub-locations. Here our results are consistent with those of Hoddinott and Skoufias (2004), and Skoufias et al. (2009), who found that a one percent rise in income resulted in an increase of 15 percentage points in the consumption of foods rich in nutrients, vitamins, and minerals in Mexico and Tanzania, respectively.

Table 19: Impact of the HSNP on consumption of nutrients, HSNP 2011 sample only analysis

Outcome variables	**HSNP poor beneficiary [Intention to treat (ITT) effects]**	**HSNP non-poor, non-beneficiary [Indirect treatment effects (ITE)]**
Energy (Kcal)	0.06 (0.04) [0.26]	0.04 (0.05) [0.45]
Protein (g)	0.05 (0.06) [0.11]	–0.03 (0.06) [0.17]
Fat (g)	–0.03 (0.08) [0.14]	–0.04 (0.09) [0.31]
Carbohydrate (g)	0.10* (0.05) [0.34]	0.10 (0.06) [0.47]
Fibre (g)	0.11 (0.07) [0.14]	0.08 (0.08) [0.25]
Zinc (mg)	–0.01 (0.05) [0.12]	–0.05 (0.05) [0.16]
Calcium (mg)	0.21* (0.11) [0.17]	0.20 (0.12) [0.30]
Heme iron (mg)	0.14 (0.30) [0.24]	–0.21 (0.31) [0.20]
Non-heme iron (mg)	0.17** (0.07) [0.17]	0.16** (0.07) [0.32]
Vitamin A (mcg RAE)	0.83*** (0.27) [0.16]	0.48* (0.25) [0.24]
Vitamin B_{12} (mcg)	0.20 (0.24) [0.10]	–0.13 (0.27) [0.09]
Vitamin C (mg)	1.09*** (0.28) [0.26]	0.97*** (0.31) [0.35]
Food folate (mcg)	0.14* (0.08) [0.14]	0.11 (0.09) [0.21]
Riboflavin (mg)	0.34* (0.20) [0.15]	0.27 (0.19) [0.29]
Beta carotene (mcg)	0.93*** (0.26) [0.17]	0.96*** (0.27) [0.28]
Observations	**2,861**	**1,762**

Notes: Coefficients are shown with robust standard errors (in parentheses) clustered at sub-location level; R-squared are in square brackets; *, ** and *** denote significance at 10%, 5%, and 1% levels, respectively. We controlled for attrition using household weights as provided in the dataset. Variables included in the regression, but not shown here for brevity, include the HSNP (dummy), which equals one if a household resides in a sub-location selected to start receiving the transfer and zero otherwise. Baseline covariates are household size per adult equivalent; ownership of a production asset (dummy); gender of a household head (dummy); age and age squared (in years) of a household head; marital status of household head (dummy); household head main economic activity (dummy); any member of the household participating in an employment program giving food or cash for work (dummy); district dummies with Turkana as the base district. Columns 2 and 3 are the HSNP 2011 poor beneficiary and non-poor, non-beneficiary households, respectively; OLS estimates are derived from the HSNP 2011 sample only.

In addition, we observe a positive and statistically significant increase in the consumption of foods rich in vitamins and minerals among the HSNP poor beneficiary compared to non-poor, non-beneficiary households (Table 19, column 2 and 3). Specifically, receipt of HSNP transfer allowed HSNP poor beneficiary households in treated sub-locations to increase their consumption of diets rich in vitamin A, vitamin C , food folate, Riboflavin and beta carotene by 83, 109, 14, 34 and 93 percentage points, respectively, after 12 months of implementation of HSNP programme, compared to those in the control sub-locations. Interestingly, the HSNP non-poor, non-beneficiary households in treated sub-locations tend to consume more nutritious foods (especially those rich in vitamin A, vitamin C and Beta carotene) by 48, 97 and 96 percentage points than those in control sub-locations. By comparison, we show that HSNP poor households tend to consume more minerals rich diets (especially Beta Carotene) compared to HSNP non-poor households.

As discussed in the estimation strategy, the OLS estimates disregard the fact that about 3% of households did not receive the HSNP transfers, so they do not account for non-compliance problems. Our preferred results are those derived from the DID estimates.

4.6.2. Impact of the HSNP on the consumption of nutrients, DID approach

In Table 20, we present regression outputs when macro and micronutrients are selected as outcome variables. Our results from ITT and ToT show that estimates of 5 outcome variables (energy, carbohydrates, calcium, heme, and non-heme iron) were statistically insignificant at conventional levels for HSNP households in treated compared to those in control sub-locations. However, the estimates are lower compared to OLS estimates, suggesting some level of bias in OLS estimates. Estimates derived from OLS regression overestimate the amount of nutrients consumed by up to 25% except heme iron which it underestimates by 33%. Furthermore, we find that HSNP poor beneficiary households in treated sub-locations tend to consume diets rich in proteins and fats than those in control sub-locations (Table 20). Specifically, we find that receipt of HSNP transfer results in about 5 and 10 percentage points rise in consumption of proteins and carbohydrate-dense diets, respectively. These results are not statisticaly significant at conventional levels. These nutrients are sourced from cereal products, thus pointing to the fact that HSNP poor beneficiary households are income poor. The expenditure shares of food are almost identical between these two periods: 76 vs 77 in 2010 and 79 vs 80 in 2011 for HSNP non-poor, non-beneficiary and poor beneficiary, respectively.

Table 20: Impact of HSNP on the consumption of macro and micronutrients

Outcome variables	**ITT effect**	**Treatment on the Treated (ToT) effects**		**HSNP non-poor, non-beneficiary**
	HSNP X Post	**HSNP X Post**	**HSNP index X Post**	**ITE**
Macronutrients				
Energy (KCal)	0.05 (0.06) [0.27]	0.04 (0.06) [0.27]	0.05 (0.06) [0.27]	0.05 (0.08) [0.39]
Protein (g)	0.05 (0.08) [0.10]	0.04 (0.08) [0.10]	0.06 (0.09) [0.10]	0.02 (0.09) [0.13]
Fat (g)	–0.01 (0.11) [0.14]	–0.03 (0.11) [0.14]	–0.02 (0.11) [0.14]	0.12 (0.14) [0.25]
Carbohydrate (g)	0.10 (0.07) [0.36]	0.09 (0.07) [0.36]	0.08 (0.07) [0.36]	0.07 (0.09) [0.43]
Fibre (g)	0.06 (0.10) [0.15]	0.05 (0.10) [0.15]	0.05 (0.11) [0.15]	0.06 (0.12) [0.19]
Micronutrients				
Zinc (mg)	0.00 (0.06) [0.11]	–0.01 (0.06) [0.11]	0.00 (0.07) [0.11]	–0.02 (0.06) [0.15]
Calcium (mg)	0.18 (0.12) [0.19]	0.16 (0.11) [0.19]	0.16 (0.12) [0.19]	0.14 (0.14) [0.26]
Heme iron (mg)	0.35 (0.35) [0.14]	0.32 (0.34) [0.14]	0.40 (0.37) [0.14]	0.03 (0.30) [0.14]
Non-Heme iron (mg)	0.09 (0.11) [0.16]	0.08 (0.11) [0.16]	0.07 (0.11) [0.16]	0.02 (0.12) [0.23]
N	**5,722**	**5,722**	**5,722**	**3,524**

Notes: Coefficient estimates are shown with robust standard errors (in parenthesis) clustered at sub-location level; R-squared are in square brackets; *, ** and *** denote significance at 10%, 5%, and 1% level, respectively; difference-in-difference estimation. We controlled for attrition using household weights as provided for in the dataset; Variables included in the regression but not shown here for brevity include HSNP (dummy) which equals one if a household resides in a sub-location selected to receive a transfer (column 2) while in columns 3 and 4 are a dummy which equals one if a household reported having received the transfer and HSNP intensity index respectively; baseline covariates are household size per adult equivalent; ownership of a production asset (dummy); gender of a household head (dummy); age and age squared (in years) of a household head; marital status of household head (dummy); household head main economic activity (dummy); any member of the household participating in employment program giving food or cash for work (dummy); district dummies with Turkana as a base district.

Additionally, we find that HSNP poor beneficiary in treated sub-locations increased their consumption of foods rich in Calcium and heme iron compared to those in control sub-locations. We show, in Table 20 (column 2), that HSNP poor beneficiary households in treated sub-locations increased consumption of non-heme iron by 9 percentage points due to receipt of HSNP transfer compared to those in control sub-locations. This result is not significant at conventional levels (i.e., P<0.1). In general, we show that HSNP poor beneficiary households in treated sub-locations seem to substitute cereals with animal-based diets compared to those residing in control sub-locations. This finding is consistent with the fact that about 70% of HSNP households practice agricture (i.e., nomadic pastoralism) as their main economic activity (See Table 17).

At the same time, we find that HSNP poor beneficiary households in treated sub-locations reduced their consumption of foods that are rich in carbohydrate, fibre and energy by between 8 and 26 percentage points as a result of receiving HSNP transfer compared to those in control areas (Table 20, column 2). Moreover, households increased consumption of zinc, calcium, heme and non-heme iron-based foods by between 6 and 25 percentage points as a result of receiving receiving HSNP transfer. These result are not significant at conventional levels (i.e., P<0.1). In general, we do not observe any significant consumption of micro and macronutrients among HNSP non-poor, non-beneficiary households during the survey period. This might be due to the effect of drought which has reduced the purchasing power of HSNP poor beneficiary households in treated sub-locations, thereby resulting in fewer transfers.[110]

Finally, we show that ITT and ToT effects are almost similar when participation is measured as an index – HSNP intensity index (under ToT estimation, Table 20, column 4), implying that household food consumption can also increase even when they do not receive the transfer. This is possible and it underlines the important role social networks play in helping poor households smooth consumption when faced with shocks. Interestingly, we also observe a similar pattern among HSNP non-poor, non-beneficiary households (Table 20, column 5).

[110] The total amount of private transfer received by households reduced by about 53.5% (i.e., from 5.55 in 2010 to 2.58 in 2011).

4.6.3. Impact of the HSNP on vitamins and minerals consumption

We present the result of an analysis in which vitamins and minerals are used as outcome variables. In Table 21, we provide the result of the HSNP poor beneficiary households using ITT and ToT effect specifications (in columns 2, 3, and 4). For the ToT estimates, actual HSNP participation is captured first as a dummy variable (column 3) and as an intensity index (column 4). In Table 21, column 5, we provide results from indirect treatment effects (ITE) obtained using HSNP non-poor, non-beneficiary households. In all regression, covariates are included.

One important pattern (from Table 21) is that HSNP poor beneficiary households in treated sub-locations significantly increased their consumption of animal products compared to those in the control sub-locations. Specifically, we find that participation in HSNP for the poor beneficiary households in treated sub-locations resulted in an increase of about 96 percent in the consumption of vitamins A compared to those in the control sub-locations. At the same time, they increased consumption of vitamin C by about 51 percent compared to households in the control sub-locations (column 5). These results are statistically significant at conventional levels. These minerals are abundant in animal proteins which are consumed mainly by richer households. Our results for vitamins A and C are similar to Skoufias et al. (2009) findings, who showed that Mexican households increased their consumption of vitamins A by 0.8 and vitamin C by 0.69 percentage points compared to those in control villages as a result of social safety net transfers. In another study, Hoddinott and Skoufias (2004) showed that PROGRESA-poor beneficiary households in treated villages increased their consumption of vitamins A and C (found in fruit, vegetables, and animal products) by about 12 percentage points compared to those in the control sub-locations.

Table 21: Impact of HSNP on vitamins and minerals consumption

Outcome variables	**ITT effect** **HSNP X Post**	**ToT effect**		**HSNP non-poor, non-beneficiary (ITE)**
		HSNP X Post	**HSNP index X Post**	**HSNP X Post**
Vitamin A (mcg RAE)	0.96*** (0.34) [0.14]	0.89*** (0.32) [0.14]	1.00*** (0.33) [0.14]	0.69* (0.39) [0.17]
Vitamin B_{12} (mcg)	0.44 (0.30) [0.11]	0.41 (0.28) [0.11]	0.48 (0.32) [0.11]	0.10 (0.28) [0.12]
Vitamin C (mg)	0.51* (0.29) [0.22]	0.53* (0.29) [0.22]	0.49 (0.44) [0.31]	0.12 (0.48) [0.31]
Food folate (mcg)	0.05 (0.13) [0.10]	0.03 (0.13) [0.10]	0.04 (0.14) [0.11]	0.08 (0.14) [0.12]
Riboflavin (mg)	0.11 (0.26) [0.21]	0.11 (0.26) [0.21]	0.14 (0.26) [0.21]	0.03 (0.23) [0.33]
Beta carotene (mcg)	0.61** (0.26) [0.13]	0.58** (0.26) [0.13]	0.60** (0.24) [0.13]	0.45 (0.36) [0.22]
N	**5,722**	**5,722**	**5,722**	**3,524**

Notes: Coefficient estimates are shown with robust standard errors (in parenthesis) clustered at the sub-location level; R-squared are in square brackets; *, ** and *** denote significance at 10%, 5%, and 1% level, respectively; difference-in-difference estimation. We controlled for attrition using household weights as provided in the dataset. Variables included in the regression, but not shown here for brevity, include the HSNP (dummy), which equals one if a household resides in a sub-location selected to receive a transfer (column 2), while in columns 3 and 4, the HSNP is captured as a dummy, which equals one if a household reported having received the transfer and as an intensity index, respectively. Baseline covariates are household size per adult equivalent; ownership of a production asset (dummy); gender of a household head (dummy); age and age squared (in years) of a household head; marital status of a household head (dummy); a household's head main economic activity (dummy); any member of a household participating in an employment program giving food or cash for work (dummy); district dummies, with Turkana as the base district.

Finally, we show that HSNP poor beneficiaries in treated sub-locations increased consumption of Beta carotene by 61 percent compared to those in control sub-locations. At the same time, we find that HSNP non-poor, non-beneficiary households in treated sub-locations increased consumption of Vitamin A rich diets compared to households residing in control sub-locations. As a robustness check, we also estimate the effects of receipt of HSNP transfer on food expenditure. This is important because by estimating the amount of nutrients consumed, one needs the quantity of food and the total expenditure on every food item. This implies that if the estimated effects on nutrients are significant, we also expect to see this in food expenditure.

We find a significant increase in the expenditure on food in both HSNP poor beneficiary and HSNP non-poor, non-beneficiary households by approximately 7 percentage points (See appendix 4.1 for HSNP household classification). These results are statistically insignificant at conventional levels and they do not vary, even when we take into account the panel nature of our dataset (Table 3A, column 3, in appendix 4.2). The rise in expenditure is highest for animal products. For food share, HSNP poor beneficiary households in treated sub-locations increased the food share in their budget allocations by about 8 percentage points compared to HSNP poor beneficiary households in control sub-locations (see Table 3A, column 4, in Appendix 4.2).

4.7. Alternative pathways that might cause potential household consumption to rise

A possible rise in a household's consumption may be caused by factors other than the HSNP transfer. For instance, increased consumption may be a result of a rise in labour earnings (Y^l), goods market (Y^g), low savings (S), higher loans and transfers (L), and, lastly, a rise in investment (I) opportunities. To understand how these factors impact the consumption of nutrients, we apply Angelucci-De Giorgi accounting identity (Angelucci and De Giorgi, 2009).

$$\Delta Y^l + \Delta Y^g + \Delta L = \Delta C + \Delta S + \Delta I \quad (3.4)$$

In equation (3.4), Δ captures both direct and indirect impact of each variable – which includes labour income, goods market, savings, loan and transfers and investment. As a first step, we test whether the receipt of the HSNP changed HSNP poor beneficiary and HSNP non-poor, non-beneficiary households' labour market participation. This is because if households increase their labour market participation, their total income will increase, and this is likely to cushion them from shocks. In Table 7A (in the appendix 4.2), we report estimates of the treatment effects for HSNP poor beneficiary and non-poor, non-beneficiary households and show that residing in an HSNP-treated sub-location reduces the likelihood of household members' participation in the labour market by 4 percentage points compared to households in control sub-locations. This result is insignificant at conventional levels (i.e., $P<0.1$). Our result mirror Holtz-Eakin, Joulfaian, & Rosen, (1993) and Joulfaian & Wilhelm, (1994) findings that heirs receiving or expecting to receive inheritance tends to lower their labour supply or work less hours. For HSNP non-poor, non-beneficiary households, our result is also not statistically different from zero, implying that a decrease (of about 2 percentage points) in consumption of nutrients among HSNP non-poor, non-beneficiary households in treated sub-locations compared to those in control sub-locations are not caused by higher labour earnings.

Secondly, we test whether the receipt of the HSNP affects the prices of major food items in treated and control sub-locations. The HSNP works through two channels to influence a household's expenditure pattern. First, if the transferred amount is large enough, it could increase the price of food items in treated compared to control sub-locations, which is a negative and undesired effect. Second, a rise in the price of food may force a household to substitute items that have risen in price, with alternative, cheaper options, probably also nutrient-dense items because of their increased income. In Tables 8A and 8B (in appendix 4.2), we compare the mean prices of food items in control and treated sub-locations. Our results show that HSNP poor beneficiary households in treated sub-locations in 2011 did not face systematically higher prices than those in control sub-locations. While we find a significant rise in prices in treated sub-locations for maize grain, loose rice, fresh milk, and kale, we also observe significantly lower prices for beans, cooking oils, sugar, and tea leaves. Equally, four items (cabbages, beef, mutton, and wheat flour) did not increase in price in 2011. Although the higher prices in treated sub-locations for maize grain, loose rice loose, fresh milk, and kale did affect the non-poor, non-beneficiary households, they benefited from the lower prices for cooking oil, sugar, cabbages, and tea leaves. Overall, the differences are usually small for all food items. We, therefore, conclude that a rise in the consumption of nutrients is not caused by low prices in HSNP non-poor, non-beneficiary sub-locations. Our result is consistent with those documented by Angelucci and De Giorgi (2009), Attanasio and Lechene (2010), and Hoddinott, Skoufias, and Washburn, (2000).

Table 8A: Comparing community prices of major food items in 2010 and 2011 and between HSNP poor beneficiary in treated and control sub-locations

	2010			**2011**		
	Control (N=1,430)	**Treated (N=1,431)**	**Diff (SD)**	**Control (N=1,368)**	**Treated (N=1,431)**	**Diff (SD)**
HSNP poor beneficiary						
Maize grain	40.73 (15.13)	42.00 (15.82)	–1.27 (0.58) **	51.55 (19.58)	59.28 (31.69)	–7.73 (1.19) ***
Dried beans	75.85 (17.98)	75.65 (18.53)	0.20 (0.68)	131.02 (194.39)	90.55 (37.38)	40.48 (5.24) ***
Wheat flour	71.92 (15.67)	73.78 (19.74)	–1.86 (0.67)	75.37 (23.46)	75.98 (18.75)	–0.61 (0.80)
Rice loose	69.10 (9.94)	74.76 (13.20)	–5.66 (0.44) ***	81.25 (17.45)	125.42 (177.72)	–44.17 (4.83) ***
Fresh milk	54.83 (26.77)	76.85 (99.95)	–22.01 (2.74) ***	61.96 (28.75)	64.67 (32.59)	–2.72 (1.16) ***
Goat/sheep meat	180.10 (44.56)	171.75 (50.59)	8.34 (1.78) ***	241.06 (86.19)	239.16 (70.96)	1.90 (3.01)
Beef	173.14 (61.66)	165.95 (69.71)	7.19 (2.46) **	220.86 (83.40)	207.64 (65.60)	13.22 (2.86)
Cooking oils	143.19 (28.00)	146.16 (32.60)	–2.97 (1.14) **	210.89 (82.02)	190.96 (60.73)	19.93 (2.75) ***
Sugar	102.90 (16.35)	101.36 (16.59)	1.54 (0.62) *	147.90 (63.07)	141.36 (55.34)	6.55 (2.26) **
Kale	13.24 (7.07)	11.40 (2.67)	1.84 (0.20) ***	16.21 (7.70)	19.29 (9.11)	–3.08 (0.32) ***
Cabbages	80.98 (35.41)	80.07 (33.32)	0.91 (1.29)	54.06 (30.84)	54.91 (26.83)	–0.85 (1.10)
Tea leaves	49.30 (61.89)	43.86 (43.90)	5.44 (2.01) **	161.88 (149.37)	123.98 (82.84)	37.90 (4.60) ***

Notes: Significance level *P<0.1; **P<0.05; ***P<0.001; student t-test; standard errors are in parenthesis. All prices are in Kenyan shillings per kilogram or per litre (for liquids); SD is the standard deviation; Diff is the difference between control and treated sub-locations.

Table 8B: Comparing community prices of major food items in 2010 and 2011 and between HSNP non-poor, non-beneficiary in treated and control sub-locations

	2010			2011		
	Control (N=885)	**Treated (N=877)**	**Diff (SD)**	**Control (N=847)**	**Treated (N=833)**	**Diff (SD)**
HSNP non-poor, non-beneficiary						
Maize grain	38.75 (11.16)	42.57 (17.57)	–3.82 (0.70) ***	50.43 (14.65)	62.64 (37.05)	–12.22 (1.37) ***
Dried beans	75.34 (17.21)	74.40 (16.40)	0.94 (0.80)	90.67 (29.12)	89.77 (24.70)	0.90 (1.32)
Wheat flour	71.06 (16.25)	69.84 (12.32)	1.22 (0.69)	76.61 (24.79)	76.60 (20.04)	0.01 (1.10)
Rice loose	70.71 (12.79)	74.21 (13.21)	–3.51 (0.62) ***	82.21 (17.83)	88.64 (39.51)	–6.43 (1.49) ***
Fresh milk	67.84 (58.68)	49.03 (27.63)	18.81 (2.19) ***	60.99 (19.10)	68.65 (47.60)	–7.66 (1.76) ***
Goat/sheep meat	179.57 (44.58)	169.15 (51.91)	10.43 (2.31) ***	240.37 (86.70)	236.27 (69.50)	4.10 (3.84)
Beef	173.04 (51.74)	164.08 (47.40)	8.96 (2.37) ***	218.57 (83.64)	212.80 (92.48)	5.78 (4.30)
Cooking oils (liquid)	144.43 (26.58)	147.12 (32.43)	–2.69 (1.41) *	212.28 (84.28)	192.36 (59.89)	19.92 (3.57) ***
Sugar	102.89 (16.65)	100.83 (16.78)	2.06 (0.80) **	147.90 (63.94)	141.11 (53.18)	6.79 (2.87) **
Kale	13.46 (7.13)	11.56 (2.76)	1.91 (0.26) ***	16.37 (7.56)	19.112 (9.16)	–2.75 (0.41) ***
Cabbages	78.15 (35.83)	78.67 (33.72)	–0.52 (1.66)	55.65 (29.88)	52.75 (27.23)	2.90 (1.40) **
Tea leaves	50.35 (60.13)	44.96 (43.48)	5.39 (2.50) **	163.64 (155.73)	125.42 (82.88)	38.22 (6.10) ***

Notes: Significance level *P<0.1; **P<0.05; ***P<0.001; student t-test; standard errors are in parenthesis. All prices are in Kenyan shillings per kilogram or per litre (for liquids); SD-standard deviation; Diff is the difference between control and treated sub-locations.

Third, we investigate whether participating in the HSNP impacts a household's likelihood of having positive savings (using the Probit model) and the amount of savings held by these households (using a DID specification). This is because HSNP households are income poor and have limited savings to cushion them against shocks. We found that both HSNP poor beneficiary and HNSP non-poor, non-beneficiary households in treated sub-locations were more likely to have positive savings than those in the control sub-locations (see Table 9A, in appendix 4.2). The HSNP poor beneficiary households in treated sub-locations increased their savings by about 8 percentage points compared to those in the control sub-locations. Although this result is not statistically different from zero, it illustrates the important role of the HSNP in the lives of income-poor households in Kenya. At the same time, we observed that HSNP non-poor, non-beneficiary households in treated sub-locations experienced a reduction in their savings by about 72 percentage points compared to those in the control areas (see Table 9A in appendix 4.2). These results are not significant at conventional levels. However, they are consistent with the idea that HSNP non-poor, non-beneficiary households are richer and might be donating some income to poorer households.

Finally, we test whether the receipt of the HSNP impacts stock levels held by households. Animals herds can be thought of as household's investment latent options, which can be used as a buffer against income shocks. We compared changes in stock levels in 2010 and 2011 in treated and control sub-locations. Our results show that, for HSNP poor beneficiary households in treated sb-locations, the number of cattle and sheep decreased marginally, while poultry, goats, camels, and donkeys increased compared to those in control sub-locations (see Table 10A in appendix 4.2). HSNP Non-poor, non-beneficiary households in treated sub-locations, on the other hand, decreased their stock levels of cattle, goats, sheep, donkeys, and poultry – there was a marginal increase only in the stock of camels compared to households in control sub-locations. It seems that HSNP non-poor, non-beneficiary households were sharing some of their livestock – especially goats, donkeys, and poultry – with HSNP poor beneficiary households at the start of the program.

4.8. Heterogeneous treatment effects of the HSNP on nutrient consumption

We analyse the effect income had on the consumption of nutrients by nutrient sources.[111] This is because households could have been substituting their self-produced foods with market-sourced foods. This can be thought of as a positive effect given that market-sourced foods tend to be more processed and their supply more reliable, especially when farmers experience sudden changing weather patterns such as drought or floods, which negatively affect their self-production capacity. We observe that HSNP poor beneficiary households in treated sub-

[111] In the questionnaire, households reported on the three main sources of the nutrients they consume, namely, from own production, market purchases, and in-kind donations. In-kind sources of nutrients are those obtained through bartering, aid, donations, and personal gifts.

locations sourced most of their micro-nutrients, vitamins and minerals (like non-heme iron, vitamin A, and beta carotene) from the market compared to those in control sub-locations (See Table 12A, in appendix 4.2). Foods sourced from the market tend to be either refined, processed and/or fortified with nutrients like iron, vitamin D and calcium. Our findinds support the ongoing discussion about the importance of local markets in supplementing the food demands of rural households in the developing world. However, if the primary source of food is self-produced, appropriate policies are needed to promote cheaper food fortification initiatives to improve nutrition at the rural household level, because in rural Kenya, farm-produced foods are not fortified and thus are low in nutrients.

According to Sibhatu and Qaim (2017), a household's diet and consequently nutritional status can be impacted negatively by production cycles, especially in rural areas where rainfall patterns dictate and influence harvest size. This means that seasonal rainfall variations can have a significant effect on the nutritional status of members of poor households: nutritional levels can peak during and immediately after long rainy seasons and decline in others.

As there are two rainy seasons (long and short rains) in the HSNP districts, nutrient intakes could be higher during the longer rainy periods. If this were the case, our results might be affected by the survey month and our estimates could subsequently be biased and inconsistent. To test for the effect of the potential impact of seasonal variation on nutrient consumption, we created a dummy variable, which equalled one if a sub-location had experienced drought in the six months before the survey month, otherwise, it was zero.[112] Table 4A (in Appendix 4.2) shows that HSNP poor beneficiary households in treated sub-locations consume more foods rich in minerals compared to those in control sub-locations when they are exposed to drought. Specifically, HSNP poor beneficiary households in treated sub-locations increase (by about 144 percentage points) their consumption of foods rich in beta carotene during drought compared to those in control sub-location when exposed to drought. This result is significant at conventional levels. At the same time, HSNP poor beneficiary households in treated sub-

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[112] We also tried other specifications in which drought is measured as a dummy variable that takes the value of one if a sub-location experienced drought in the three months prior to the survey. We do not present these results here, but the trends are similar to the ones observed here. These results are available from the authors upon request.

locations tend to consume less (by up to 212 percentage points) non-heme iron dense foods than HSNP households in control sub-locations. Finally, we find evidence that HSNP poor beneficiary households in treated sub-locations reduced their consumption of fatty dense and riboflavin rich foods by 40 and 91 percentage points, respectively compared to households in control sub-locations. These findings are consistent with the hypothesis that during a drought, agricultural households tend to consume cereal-based foods, which can be stored for a long time.

Given that the HSNP districts experienced a severe drought in 2011, our results touch on an important function that food plays in the rural areas: the changes in the types of food consumed can be considered as a short term adaptation strategy for households when they are affected by climate change, through seasonal weather variability. Here, our results are contrary to those found by Ogutu et al. (2020): seasonality does not affect nutritional indicators among poor households in western Kenya. This may be the result of differences in the weather patterns of the two regions: they evaluated farmers located in medium to high rainfall areas. Additionally, in our study, the local markets are well integrated with the inclusion of food consumption from wholesale markets which give to households alternative sources of foods. These alternative sources provide households with additional options that can be accessed to diversify their food consumption patterns, in the presence of drought.

In Table 5A (in Appendix 4.2), we look at whether the targeting type (whether the HSNP is given to males or females within the households) affects resource allocation and subsequently nutrient consumption. Previous studies have shown that transfers that are targeted at women tend to be used to support household-related expenditure (especially food, education, nutrition, and healthcare). For example, Armand et al. (2020) showed that, in Macedonia, giving cash transfers to women increases expenditure on food by between 4 and 5 percentage points. In Ecuador, Schady and Rosero (2008) also found a 3 to 4 percentage point increase in food expenditure when cash transfers were targeted at women. However, for developing countries like Kenya, Shapiro et al. (2019) found little evidence of a difference in caloric and food expenditure elasticities between male and female recipients of cash transfers.[113]

As 90% of households selected through the community-based targeting (CBT) and dependency ratio (DR) mechanisms were women, we created a dummy variable, which equals one if the targeting type is either CBT or DR, and zero otherwise. This approach allowed us to capture the gender implications associated with the HSNP transfers in Kenya and their associated implications in terms of food and nutrition at sub-locational level. Our triple difference estimation (Table 5A, in Appendix 4.2) shows that HSNP poor beneficiary households selected via CBT and DR targeting methods in treated sub-locations had diets richer in micronutrients (especially calcium and heme iron), vitamins (A, B_{12} and C) and minerals (folate and beta carotene) than those selected through social pension targeting and reside in control sub-locations. This can be interpreted as a rise in expenditure on these food components. For example, we found that receipt of HSNP transfer by poor beneficiary households in treated sub-locations led to an increase of about 65 percentage points in the consumption of heme iron-dense foods compared to those those selected through social pension targeting and resided in the control sub-locations. These results are not statistically significant at conventional levels. Moreover, our result show that HSNP poor beneficiary household/individual in treated sub-locations and those selected via CBT and DR targeting methods increased (by about 26 percentage points) consumption of foods rich in calcium compared to those selected through social pension targeting and lived in the control sub-locations. Finally, we observe that HSNP poor households in treated sub-locations consume more vitamins compared to minerals compared to those in control sub-locations and were selected through social pension targeting. Although these result is not statistically different from zero, they support previous findings on the positive impact of targeting women as it tends to increase the percentage of the household budget spent on food. However, our result might have been weighed down by the presence of male-headed households in the sample, so should be interpreted with caution. Nevertheless,

[113] For overall food expenditure elasticities, they estimate the elasticity to be 0.720 and 0.715, respectively, for female and male recipients of cash transfer. For caloric elasticities, they found elasticities of 0.46 and 0.54 for female and male recipients, respectively.

there was still evidence of the positive effect of targeting women over other household members.

4.9. Conclusion

Using a randomized control trial dataset, we analysed how the receipt of a temporary income (due to HSNP participation or actual receipt of HSNP transfer) impacts the consumption of nutrients in Kenya. Our results show that HSNP poor beneficiary households in treated sub-locations significantly increased their consumption of animal products compared to those in the control sub-locations. Specifically, we find that participation in HSNP for poor beneficiary households in treated sub-locations resulted in an increase of approximately 96 percent in the consumption of vitamins A compared to those in the control sub-locations. Secondly, HSNP poor beneficiary households in treated sub-locations increased consumption of beta carotene and vitamin C by 61 and 51 percent, respectively compared to households in the control sub-locations. These results are statistically significant at conventional levels. Third, we show that HSNP poor beneficiaries in treated sub-locations increased consumption of Beta carotene by 61 percent compared to those in control sub-locations. Finally, we observe that HSNP poor beneficiary households in treated sub-locations sourced most of their nutrients, vitamins and minerals (especially heme iron, vitamin A and beta carotene) from the market. Foods sourced from the market tend to be either refined, processed and/or fortified with nutrients like iron, vitamin D and calcium.

Another important findings is that HSNP non-poor, non-beneficiary households in treated sub-locations tend to consume foods rich in vitamins and minerals compared to those in control sub-locations. Specifically, we show that HSNP non-poor, non-beneficiary households residing in treted sub-locations increase (by about 70 percent) the consumption of foods rich in vitamin A compared to those in control sub-locations. This result is statisticmally significant at conventional levels. In general, the low or no impact of the HSNP on macro-nutrient consumption is not surprising and is in line with previous studies using similar datasets. For example, Merttens et al. (2013) found that the HSNP had no impact on child growth nutrients. This finding of no impact was also confirmed by Dietrich and Shmerzeck (2020). At the same time, we observe that HSNP poor beneficiary and non-poor, non-beneficiary households tend to consume more (by up to 26 percent) non-heme iron dense foods than households in control sub-locations. On targeting, our result shows that HSNP poor beneficiary households selected via CBT and DR targeting methods in treated sub-locations had diets richer in micronutrients (especially food folate) and vitamins (A and C) than those selected through social pension targeting.

Moreover, we show that HSNP poor beneficiary households in treated sub-locations consume more foods rich in minerals compared to those in control sub-locations when they are exposed to drought. Specifically, HSNP poor beneficiary households in treated sub-locations increase (by about 144 percentage points) their consumption of foods rich in beta carotene during drought compared to those in control sub-location when exposed to drought. This result is significant at conventional levels. At the same time, HSNP poor beneficiary households in treated sub-locations tend to consume less (by up to 212 percentage points) non-heme iron dense foods than HSNP households in control sub-locations. Finally, we find evidence that HSNP poor beneficiary households in treated sub-locations reduced their consumption of fatty dense and riboflavin rich foods by 40 and 91 percentage points, respectively compared to households in control sub-locations. These findings are consistent with the hypothesis that during a drought, agricultural households tend to consume cereal-based foods, which can be stored for a long time.

4.10. Areas for further research

First, our analysis can be thought of as a short term impact of a social safety net. This means that it covered less than five years of operation. And because of this, it unlikely to find significant effect on any outcome of interest like child health indicators which requires more time to manifest. In line with this, we recommend further research to use long period datasets (datasets collected over five waves) to derive long term effect of a cash transfer. In this way, it is possible to provide a complete picture of the effect of cash transfer in the short and long run.

Secondly, we relied on strong assumption that the effect of HSNP transfer would spillover to HSNP non-poor, non-beneficiary households in treated sub-locations to derive sub-locational effects. Another important assumption is that there is no sharing between households in treated and control sub-locations. This is unlikely in rural settings where resource sharing is based on norm and religion. We use these assumptions since we lack data on sources of income to HSNP poor and non-poor households. Future work remains in using datasets where sources of household income are captured. Such information might facilitate studies of how households are interconnected in village economies.

APPENDICES TO CHAPTER FOUR

Appendix 4.1: Diagrammatic representation of HSNP households

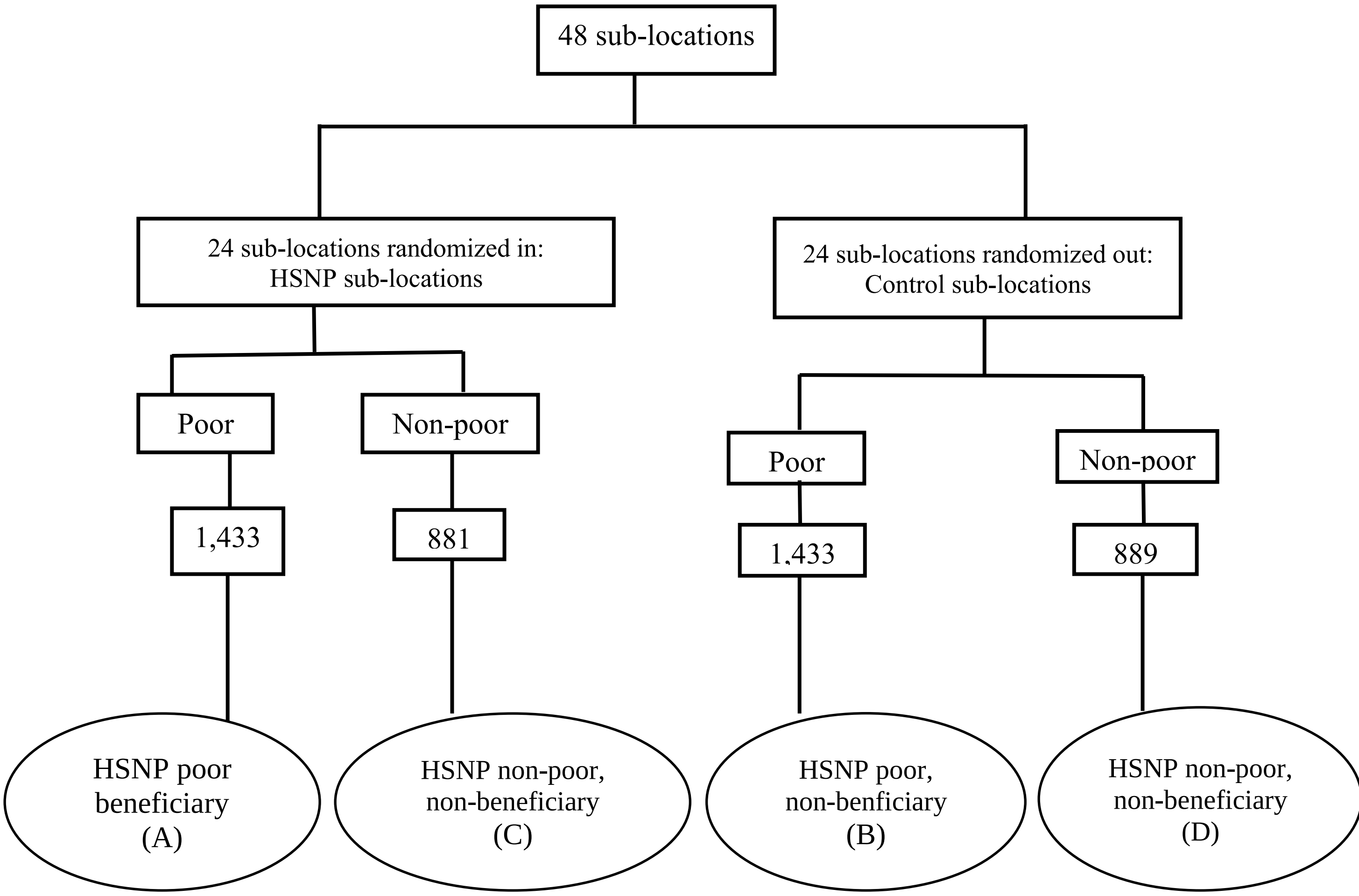

Figure S4.1: Experimental design of HSNP 2010 and 2011 panel datasets

Our impact evaluation is based on comparing households in treated and control sub-locations. For HSNP poor beneficiary households (see Figure S4.1), we compared households in treated versus control sub-locations (i.e., A versus B). Similarly, for HSNP non-poor, non-beneficiary households (see Figure S4.1), we estimate the impact through comparing HSNP non-poor, non-beneficiary in treated versus HSNP non-poor, non-beneficiary households in control sub-locations (i.e., C versus D). In the experiement, a household is considered treated if it was selected to immediately start receing HSNP transfer and is a resident of a sub-location selected as a receipient of HSNP transfer. We refer to these households as HSNP poor beneficiary households in treated sub-locations. Likewise, HSNP poor beneficiaries in control sub-locations are households selected for inclusion into HSNP but did not start receiving payments immediately after selection. Such households had to wait for 2 years before receiving HSNP transfer.

In the dataset, we have additional information on households sampled from three settlemets (i.e., main, permanent and non-permanent) within each sub-location. Following the same identification as HSNP poor beneficiary households, we call these households HSNP non-poor, non-beneficiary in treated and control sub-locations (i.e., C and D). Information from HSNP non-poor, non-benefciary households were collected only during baseline and follow-up survey (i.e., in 2011 only) to facilitate targeting analysis and the analysis of spill-over effects. We hypothesize that spill-over effects may occur either because HSNP transfer may impact local food markets or inter-household sharing arrengements . HSNP poor beneficiary and non-poor nn-beneficiary households in trated sub-locations are sharing HSNP transfer because they live in the same sub-location and are thus tied with traditional norms which often dictate that the rich should help the poor households. It is likely that neighbouring households would share the transfer received with other households who happen to be HSNP non-poor, non-beneficiary in treated sub-locations. This has been shown by previous literature shows (Merttens et al., 2013), HSNP districts have a tendency of sharing animals and other necessities, especially after drought, as a way of insuring the less fortunate members of the society within the community. We estimate the magnitude of spill-over effects by comparing trends in child nutrient consumption between HSNP poor beneficiary (and non-poor, non-beneficiary) in treated and control sub-locations over time. In doing so, we limited our data to HSNP 2010 and 2011 panel survey because information on HSNP non-poor non-beneficiary households were not collected during the HSNP 2012 survey round.

APPENDIX 4.2: Additional robustness tests

Table 3A: Impact of HSNP on food consumption expenditure and food share in total household expenditure

Variables	Food share (OLS)	Food expenditure (OLS)	Food expenditure (DID)	Food share (DID)
	(1)	**(2)**	**(3)**	**(4)**
Panel A: HSNP poor beneficiary and non-beneficiary households				
ITT	–1.68	0.05	0.07	0.08
	(1.21)	(0.07)	(0.08)	(1.40)
	[0.31]	[0.27]	[0.27]	[0.30]
Observations	**2,861**	**2,861**	**5,722**	**5,722**
Panel B: HSNP non-poor, non-beneficiary households				
ITE	–2.24	0.06	0.07	0.19
	(1.43)	(0.06)	(0.10)	(2.16)
	[0.30]	[0.37]	[0.31]	[0.29]
Observations	**1,762**	**1,762**	**3,524**	**3,524**

Notes: Robust standard errors (in parentheses) are clustered at sub-location level; significance level *** p<0.01, ** p<0.05, * p<0.1; quarterly amounts per adult equivalent; R-squared are in square brackets. Food expenditure is in monthly KES per adult equivalent. Coefficients under OLS estimation are for whether a household lives in a treated or a control sub-location, while under DID, it is the interaction between treatment and post dummy; the results are unchanged without covariates. All regression includes baseline controls similar to those used in Table 18.

Table 4A: Impact of the HSNP on the consumption of nutrients, by seasonality

Outcome variables	ITT HSNP X Post X Drought	ToT		HSNP non-poor, non-beneficiary
		HSNP X Post X Drought	HSNP Index X Post X Drought	ITE
Energy (Kcal)	–0.11 (0.14) [0.27]	-0.12 (0.14) [0.27]	–0.10 (0.14) [0.27]	0.03 (0.12) [0.40]
Protein (g)	–0.34 (0.20) [0.10]	–0.33* (0.19) [0.10]	–0.31 (0.20) [0.10]	–0.17 (0.20) [0.14]
Fat (g)	–0.40* (0.23) [0.16]	–0.43* (0.23) [0.16]	–0.44* (0.24) [0.16]	–0.16 (0.18) [0.26]
Carbohydrate (g)	0.06 (0.15) [0.37]	0.05 (0.15) [0.37]	0.08 (0.15) [0.37]	0.10 (0.16) [0.44]
Fibre (g)	0.10 (0.24) [0.18]	0.09 (0.23) [0.18]	0.10 (0.24) [0.18]	0.17 (0.23) [0.21]
Zinc (mg)	–0.26 (0.17) [0.11]	–0.26 (0.17) [0.11]	–0.24 (0.18) [0.11]	–0.08 (0.16) [0.17]
Calcium (mg)	0.30 (0.26) [0.19]	0.32 (0.25) [0.20]	0.42 (0.27) [0.20]	0.18 (0.34) [0.27]
Heme iron (mg)	–2.12** (0.81) [0.18]	–2.09** (0.79) [0.18]	–2.05** (0.80) [0.18]	–1.21 (0.94) [0.16]
Non-heme iron (mg)	0.13 (0.24) [0.19]	0.13 (0.23) [0.19]	0.16 (0.24) [0.19]	0.20 (0.17 [0.26]
Vitamin A (Mcg RAE)	0.27 (0.79) [0.14]	0.38 (0.77) [0.14]	0.58 (0.80) [0.14]	0.37 (0.91) [0.19]
Vitamin B_{12} (mcg)	–0.91 (0.63) [0.15]	–0.89 (0.61) [0.15]	–0.84 (0.63) [0.14]	–0.26 (0.70) [0.16]
Vitamin C (mg)	–0.11 (1.15) [0.24]	–0.13 (1.14) [0.24]	–0.01 (1.14) [0.24]	–2.02 (1.36) [0.34]
Folate (mcg)	0.03 (0.27) [0.12]	–0.03 (0.26) [0.12]	–0.06 (0.27) [0.12]	0.04 (0.24) [0.14]
Riboflavin (mg)	–0.91* (0.50) [0.23]	–0.88* (0.50) [0.23]	-0.84* (0.49) [0.23]	–0.74 (0.58) [0.34]
Beta carotene (mcg)	1.44*(0.80) [0.17]	1.39* (0.79) [0.17]	1.61* (0.81) [0.17]	0.84 (1.11) [0.27]
N	**5,660**	**5,660**	**5,660**	**3,486**

Notes: We used a Standardized Precipitation Evapotranspiration Index (SPEI) values in Ongudi and Thiam (2020) but classified a sub-location as experiencing drought in the last six months if SPEI value was below –0.5 and zero otherwise (Agnew, 2000). We used this drought dummy variable to capture seasonality. Coefficient estimates are shown with robust standard errors (in parenthesis) clustered at sub-location level; R-squared are in square brackets; *, ** and *** denote significance at 10%, 5%, and 1% level, respectively. We controlled for attrition using household weights. Variables included in the regression, but not shown here for brevity, include the HSNP (dummy), which equals one if a household resides in a sub-location selected to receive a transfer (column 2), in column 3 and 4, the HSNP is a dummy variable, which equals one if a household actually received the transfer and HSNP intensity index, respectively; baseline covariates are household size per adult equivalent; gender of household head (dummy); age and age squared (in years) of a household head; marital status of a household head (dummy); a household head's main economic activity (dummy); any member of a household participating in an employment program giving food or cash for work (dummy); district dummies, with Turkana as the base district.

Table 5A: Impact of the HSNP on the consumption of nutrients, by targeting type

Outcome variables	ITT HSNP X Post X Targeting	ToT		HSNP non-poor, non-beneficiary
		HSNP X Post X Targeting	HSNP Index X Post X Targeting	ITE
Energy (Kcal)	–0.08 (0.15) [0.27]	–0.09 (0.15) [0.27]	–0.12 (0.15) [0.27]	–0.13 (0.18) [0.39]
Protein (g)	0.00 (0.18) [0.10]	–0.01 (0.18) [0.10]	–0.03 (0.19) [0.10]	–0.25 (0.17) [0.14]
Fat (g)	–0.08 (0.24) [0.14]	–0.12 (0.23) [0.14]	–0.13 (0.26) [0.14]	0.02 (0.30) [0.25]
Carbohydrate (g)	–0.12 (0.16) [0.36]	–0.11 (0.15) [0.36]	–0.16 (0.15) [0.36]	–0.11 (0.23) [0.43]
Fibre (g)	–0.04 (0.23) [0.15]	–0.04 (0.22) [0.15]	–0.08 (0.22) [0.15]	–0.04 (0.27) [0.19]
Zinc (mg)	–0.00 (0.18) [0.11]	–0.02 (0.18) [0.11]	–0.05 (0.19) [0.11]	–0.14 (0.14) [0.16]
Calcium (mg)	0.26 (0.20) [0.20]	0.23 (0.19) [0.20]	0.24 (0.21) [0.20]	–0.08 (0.24) [0.28]
Heme iron (mg)	0.65 (0.60) [0.14]	0.61 (0.58) [0.14]	0.68 (0.62) [0.14]	–0.25 (0.56) [0.15]
Non-heme iron (mg)	–0.15 (0.23) [0.17]	–0.15 (0.22) [0.17]	–0.21 (0.22) [0.17]	–0.22 (0.27) [0.24]
Vitamin A (mcg RAE)	0.84 (0.90) [0.15]	0.69 (0.87) [0.15]	0.70 (0.93) [0.15]	0.57 (0.80) [0.18]
Vitamin B_{12} (mcg)	0.49 (0.49) [0.11]	0.44 (0.47) [0.11]	0.51 (0.52) [0.11]	–0.31 (0.49) [0.12]
Vitamin C (mg)	0.46 (0.52) [0.23]	0.42 (0.52) [0.23]	0.42 (0.56) [0.23]	0.36 (0.78) [0.32]
Folate (mcg)	0.19 (0.24) [0.11]	0.19 (0.24) [0.11]	0.20 (0.25) [0.11]	0.17 (0.29) [0.13]
Riboflavin (mg)	–0.05 (0.41) [0.21]	–0.04 (0.41) [0.21]	–0.04 (0.42) [0.21]	–0.28 (0.45) [0.33]
Beta carotene (mcg)	0.08 (0.80) [0.13]	0.73 (0.48) [0.13]	0.74 (0.48) [0.13]	0.39 (0.57) [0.23]
Observations	**5,722**	**5,722**	**5,722**	**3,524**

Notes: Coefficient estimates are shown with robust standard errors (in parenthesis) clustered at sub-location level; R-squared are in square brackets; *, ** and *** denote significance at 10%, 5%, and 1% level, respectively. We controlled for attrition using household weights. Variables included in the regression, but not shown here for brevity, include the HSNP (dummy), which equals one if a household resides in a sub-location selected to receive a transfer (column 2); in column 3 and 4, the HSNP is a dummy variable, which equals one if a household received the transfer and the HSNP intensity index, respectively. Baseline covariates are household size per adult equivalent; gender of a household head (dummy); age and age squared (in years) of a household head; marital status of a household head (dummy); a household head's main economic activity (dummy); any member of a household participating in an employment program giving food or cash for work (dummy); district dummies, with Turkana as a base district.

Table 7A: Effect of HSNP on labour market participation

Variables	HSNP poor beneficiary households	HSNP non-poor, non-beneficiary households
HSNP X Post	–0.04	–0.02
	(0.04)	(0.03)
Observations	**5,722**	**3,524**
Control	**Yes**	**Yes**

Notes: Robust standard errors (in parentheses) clustered at sub-location level; significance level *** p<0.01, ** p<0.05, * p<0.1; Probit regression; Coefficients are estimated at means; outcome variable is a dummy variable which equals one if anyone in the household participates in employment program giving food or cash for work; All regressions include covariates similar to those in Table 18 except that we now use the probability of a household's member participating in the labour market as a dependent variable.

Table 8a: Comparing community prices of major food items in 2010 and 2011 and between HSNP poor beneficiary in treated and control sub-locations

	2010			**2011**		
	Control (N=1430)	**Treated (N=1431)**	**Diff (SD)**	**Control (N=1368)**	**Treated (N=1431)**	**Diff (SD)**
HSNP poor beneficiary						
Maize grain	40.73 (15.13)	42.00 (15.82)	–1.27 (0.58) **	51.55 (19.58)	59.28 (31.69)	–7.73 (1.19) ***
Dried beans	75.85 (17.98)	75.65 (18.53)	0.20 (0.68)	131.02 (194.39)	90.55 (37.38)	40.48 (5.24) ***
Wheat flour	71.92 (15.67)	73.78 (19.74)	–1.86 (0.67)	75.37 (23.46)	75.98 (18.75)	–0.61 (0.80)
Rice loose	69.10 (9.94)	74.76 (13.20)	–5.66 (0.44) ***	81.25 (17.45)	125.42 (177.72)	–44.17 (4.83) ***
Fresh milk	54.83 (26.77)	76.85 (99.95)	–22.01 (2.74) ***	61.96 (28.75)	64.67 (32.59)	–2.72 (1.16) ***
Goat/sheep meat	180.10 (44.56)	171.75 (50.59)	8.34 (1.78) ***	241.06 (86.19)	239.16 (70.96)	1.90 (3.01)
Beef	173.14 (61.66)	165.95 (69.71)	7.19 (2.46) **	220.86 (83.40)	207.64 (65.60)	13.22 (2.86)
Cooking oils	143.19 (28.00)	146.16 (32.60)	–2.97 (1.14) **	210.89 (82.02)	190.96 (60.73)	19.93 (2.75) ***
Sugar	102.90 (16.35)	101.36 (16.59)	1.54 (0.62) *	147.90 (63.07)	141.36 (55.34)	6.55 (2.26) **
Kale	13.24 (7.07)	11.40 (2.67)	1.84 (0.20) ***	16.21 (7.70)	19.29 (9.11)	–3.08 (0.32) ***
Cabbages	80.98 (35.41)	80.07 (33.32)	0.91 (1.29)	54.06 (30.84)	54.91 (26.83)	–0.85 (1.10)
Tea leaves	49.30 (61.89)	43.86 (43.90)	5.44 (2.01) **	161.88 (149.37)	123.98 (82.84)	37.90 (4.60) ***

Notes: Significance level *p<0.1; **p<0.05; ***p<0.001; student t-test; standard errors are in parenthesis. All prices are in Kenyan shillings per kilogram or per litre (for liquids). SD is the standard deviation.

Table 8b: Comparing community prices of major food items in 2010 and 2011 and between HSNP non-poor, non-beneficiary in treated and control sub-locations

	2010			**2011**		
	Control (N=885)	**Treated (N=877)**	**Diff (SD)**	**Control (N=847)**	**Treated (N=833)**	**Diff (SD)**
HSNP non-poor, non-beneficiary						
Maize grain	38.75 (11.16)	42.57 (17.57)	–3.82 (0.70) ***	50.43 (14.65)	62.64 (37.05)	–12.22 (1.37) ***
Dried beans	75.34 (17.21)	74.40 (16.40)	0.94 (0.80)	90.67 (29.12)	89.77 (24.70)	0.90 (1.32)
Wheat flour	71.06 (16.25)	69.84 (12.32)	1.22 (0.69)	76.61 (24.79)	76.60 (20.04)	0.01 (1.10)
Rice loose	70.71 (12.79)	74.21 (13.21)	–3.51 (0.62) ***	82.21 (17.83)	88.64 (39.51)	–6.43 (1.49) ***
Fresh milk	67.84 (58.68)	49.03 (27.63)	18.81 (2.19) ***	60.99 (19.10)	68.65 (47.60)	–7.66 (1.76) ***
Goat/sheep meat	179.57 (44.58)	169.15 (51.91)	10.43 (2.31) ***	240.37 (86.70)	236.27 (69.50)	4.10 (3.84)
Beef	173.04 (51.74)	164.08 (47.40)	8.96 (2.37) ***	218.57 (83.64)	212.80 (92.48)	5.78 (4.30)
Cooking oils (liquid)	144.43 (26.58)	147.12 (32.43)	–2.69 (1.41) *	212.28 (84.28)	192.36 (59.89)	19.92 (3.57) ***
Sugar	102.89 (16.65)	100.83 (16.78)	2.06 (0.80) **	147.90 (63.94)	141.11 (53.18)	6.79 (2.87) **
Kale	13.46 (7.13)	11.56 (2.76)	1.91 (0.26) ***	16.37 (7.56)	19.112 (9.16)	–2.75 (0.41) ***
Cabbages	78.15 (35.83)	78.67 (33.72)	–0.52 (1.66)	55.65 (29.88)	52.75 (27.23)	2.90 (1.40) **
Tea leaves	50.35 (60.13)	44.96 (43.48)	5.39 (2.50) **	163.64 (155.73)	125.42 (82.88)	38.22 (6.10) ***

Notes: Significance level *p<0.1; **p<0.05; ***p<0.001; student t-test; standard errors are in parenthesis. All prices are in Kenyan shillings per kilogram or per litre (for liquids). SD-standard deviation.

Table 9A: Impact of HSNP participation on household savings levels

Variables	Probit	DID
Panel A: HSNP poor beneficiary households		
ITT	0.01 (0.03)	0.08 (0.23) [0.06]
Observations	**5,722**	**5,722**
Panel B: HSNP non-poor, non-beneficary households		
ITE	0.01 (0.03)	–0.72 (0.46) [0.18]
Observations	**3,524**	**3,524**

Notes: Robust standard errors (in parentheses) are clustered at the sub-location level; significance level *** p<0.01, ** p<0.05, * p<0.1; outcome vriables are quarterly amounts per adult equivalent and are expressed in logarithm; R-squared are in square brackets; All regressions include covariates similar to those in Table 18.

Table 10A: Treatment effect on the average monthly change in the stock of animals

Variables	Cattle	Goat	Camel	Sheep	Donkey	Poultry
Average treatment effects (ATE) (N=2,861)						
HSNP	–0.02	0.05	0.02	–0.04	0.00	0.00
	(0.06)	(0.42)	(0.04)	(0.15)	(0.00)	(0.01)
Indirect treatment effects (ITE) (N=1,762)						
HSNP	–0.03	–0.03	0.01	–0.06	–0.01	–0.02
	(0.06)	(0.34)	(0.05)	(0.15)	(0.02)	(0.02)

Notes: Monthly averages (in numbers) are computed by dividing a change in the stock of animals between 2010 and 2011 by the number of months between them (in this case 12 months). Standard errors (in parentheses) are clustered at the sub-location level. First difference estimation; significance level *** p<0.01, ** p<0.05, * p<0.1.

Table 11A: Per Capita nutrient consumption expenditure of the top and bottom percentile groups

Outcome variables	HSNP poor beneficiary households				HSNP non-poor, non-beneficiary households			
	Treated		Control		Treated		Control	
	p25	p75	p25	p75	p25	p75	p25	p75
Energy (Kcal)	10756.54	20043.96	11229.50	20772.84	12720.77	23275.75	12146.19	25399.50
Protein (g)	319.18	611.52	306.75	653.84	356.46	691.00	335.23	797.32
Fat (g)	175.47	371.85	167.22	405.89	196.48	438.95	196.48	494.50
Fibre (g)	197.60	418.00	207.19	436.16	222.06	473.01	215.85	477.89
Carbohydrate (g)	1683.83	3343.09	1781.85	3454.92	2003.67	3928.71	1959.85	4154.22
Zinc (mg)	52.71	100.26	54.16	103.30	59.21	114.01	58.64	123.85
Calcium (mg)	1727.50	4492.69	1789.50	4388.87	2025.38	5681.43	1998.49	6056.02
Iron (mg)	80.36	163.90	78.04	159.70	90.11	191.39	86.23	184.09
Heme iron (mg)	0.85	18.48	0.83	16.07	1.21	22.81	1.38	27.40
Vitamin A (mcg RAE)	221.88	1015.13	251.41	1067.80	336.20	1389.70	287.54	1482.14
Vitamin B_{12} (mcg)	4.18	19.21	4.33	19.35	5.98	23.60	6.67	27.23
Vitamin C (mg)	2.40	113.23	2.33	38.58	2.99	143.88	3.11	69.75
Food folate (mcg)	1,822.19	4257.03	1932.85	4519.50	2009.17	4628.71	2016.96	4951.09
Riboflavin (mg)	9.14	65.81	9.16	52.76	11.28	80.34	10.47	66.18
Beta carotene (mcg)	238.48	1197.16	224.24	900.90	272.64	1455.47	254.66	1000.57
Observations	**1,431**	**1,431**	**1,430**	**1,430**	**877**	**877**	**885**	**885**

Table 12A: Impact of the HSNP on the consumption of nutrients, by nutrient source

Outcome variables	HSNP poor beneficiary households			HSNP non-poor, non-beneficiary households		
	Production	Market	In-kind	Production	Market	In-kind
	HSNP X Post	HSNP X Post	HSNP Index X Post	HSNP Index	HSNP Index	HSNP Index
Energy (Kcal)	0.69 (0.50) [0.24]	0.45 (0.44) [0.20]	–1.25 (0.91) [0.21]	0.41 (0.66) [0.31]	–0.19 (0.43) [0.22]	0.14 (1.00) [0.19]
Protein (g)	0.33 (0.33) [0.25]	0.47 (0.35) [0.24]	–0.80 (0.58) [0.23]	0.22 (0.45) [0.32]	–0.23 (0.32) [0.23]	–0.02 (0.62) [0.20]
Fat (g)	0.41 (0.31) [0.24]	0.77 (0.52) [0.14]	–0.71 (0.56) [0.23]	0.35 (0.41) [0.31]	–0.17 (0.40) [0.15]	0.24 (0.63) [0.20]
Carbohydrate (g)	0.58 (0.38) [0.19]	0.43 (0.37) [0.25]	–1.10 (0.79) [0.22]	0.58 (0.50) [0.24]	–0.09 (0.35) [0.26]	0.01 (0.79) [0.18]
Fibre (g)	-0.17 (0.25) [0.08]	0.62 (0.38) [0.19]	–0.79 (0.64) [0.23]	–0.04 (0.17) [0.11]	–0.13 (0.31) [0.17]	0.17 (0.67) [0.19]
Zinc (mg)	0.18 (0.22) [0.25]	0.48 (0.31) [0.24]	–0.59 (0.44) [0.24]	0.14 (0.32) [0.31]	–0.20 (0.27) [0.23]	0.08 (0.46) [0.20]
Calcium (mg)	0.75 (0.54) [0.22]	0.39 (0.36) [0.29]	–0.91 (0.70) [0.23]	0.68 (0.68) [0.28]	–0.36 (0.42) [0.30]	–0.10 (0.76) [0.20]
Heme iron (mg)	0.09 (0.16) [0.24]	0.21 (0.28) [0.19]	0.04 (0.10) [0.05]	0.01 (0.29) [0.32]	–0.13 (0.21) [0.25]	0.06 (0.17) [0.10]
Non-heme iron (mg)	–0.20 (0.23) [0.08]	0.62* (0.33) [0.23]	–0.59 (0.52) [0.24]	–0.04 (0.11) [0.11]	–0.11 (0.27) [0.21]	0.10 (0.55) [0.19]
Vitamin A (Mcg RAE)	0.63 (0.46) [0.22]	0.96** (0.37) [0.26]	–0.39 (0.38) [0.23]	0.57 (0.61) [0.27]	0.12 (0.40) [0.32]	–0.42 (0.45) [0.20]
Vitamin B_{12} (mcg)	0.30 (0.19) [0.23]	0.30 (0.25) [0.34]	–0.03 (0.09) [0.06]	0.26 (0.30) [0.30]	–0.15 (0.28) [0.33]	–0.11 (0.10) [0.10]
Vitamin C (mg)	0.24 (0.22) [0.09]	0.54 (0.37) [0.29]	–0.31 (0.29) [0.22]	0.38 (0.47) [0.15]	–0.05 (0.51) [0.30]	–0.13 (0.33) [0.14]
Folate (mcg)	0.57 (0.35) [0.21]	0.64 (0.46) [0.18]	–0.98 (0.83) [0.23]	0.54 (0.49) [0.26]	–0.14 (0.42) [0.17]	0.18 (0.92) [0.19]

Riboflavin (mg)	0.17 (0.15) [0.23]	0.26 (0.22) [0.28]	–0.27 (0.22) [0.26]	0.24 (0.19) [0.27]	–0.03 (0.24) [0.37]	0.02 (0.20) [0.20]
Beta carotene (mcg)	0.54 (0.45) [0.19]	1.03** (0.44) [0.26]	–0.94 (0.61) [0.21]	0.61 (0.55) [0.21]	0.01 (0.57) [0.29]	–0.65 (0.66) [0.16]
N	**5,722**	**5,722**	**5,722**	**3,524**	**5,722**	**5,722**

Notes: Coefficient estimates are shown with robust standard errors (in parenthesis) clustered at sub-location level; R-squared are in square brackets; *, ** and *** denote significance at 10%, 5%, and 1% level, respectively. We controlled for attrition using household weights. Variables included in the regression, but not shown here for brevity, include the HSNP (dummy), which equals one if a household resides in a sub-location selected to receive a transfer and zero otherwise; household size per adult equivalent; gender of a household head (dummy); age and age squared (in years) of a household head; marital status of a household head (dummy); a household head's main economic activity (dummy); any member of a household participating in an employment program giving food or cash for work (dummy); district dummies, with Turkana as a base district.

CHAPTER 5: CONCLUSION

5.1. Summary of findings

This thesis focusses on three inter-related questions in the field of development economics and climate change literature: (i) How does exposure to weather-related shocks (in this case drought) impact a child's health? (ii) Does participating in a public transfer program (in the form of HSNP) crowd out or crowd in informal transfer received by rural households? And finally, (iii) What is the effect of income on consumption of nutrients? These questions are answered using Kenya as a case study and are organized into three distinct papers making up this thesis.

In the first paper, we assess the effect of drought exposure on child health indicators (proxied by height for age and weight for age Z-scores). Our findings show that cumulative drought exposure has much higher effect than drought exposure during the in-utero period. Our result from in utero period is contrary to the idea that interventions during early stages of life might have higher returns than those in later life. This means that interventions during this critical window (during in-utero) might not have higher returns than those undertaken in later periods of life as reported in previous studies. In addition, we provide evidence that confirms that exposure to drought worsens child HAZ and WAZ scores. Specifically, we show that HSNP poor beneficiary households in treated sub-locations and those that were exposed to cumulative drought reported lower (by about 50 percentage points) HAZ scores compared to those in control sub-locations. For WAZ scores, we show that HSNP poor beneficiary households in treated sub-locations reported worse WAZ scores by approximately 29 percentage points compared to those in control sub-location and when drought is measured in utero. Comparatively, we find that participation in HSNP (i.e., when HSNP is measured as a dummy variable) had stronger effect than when HSNP is measured as number of months of exposure. We find evidence that shows that receiving HSNP transfer buffers the negative effects of cumulative drought on child's HAZ scores. Specifically, HSNP poor beneficiary households residing in treated sub-locations observed an improvement in HAZ scores by 74 percent compared to those in control sub-locations when drought is measured in cumulative terms. This result is statistically significant at conventional levels (i.e., $P<0.1$). For drought exposure during in-utero period, we find evidence that shows that there is possibility of remediation on

WAZ scores for HSNP poor beneficiary households in treated compared to those in control sub-locations. Our results highlight the need to put more emphasis on the support delivered to poor households to assist them mitigate the deleterious effects associated with weather shocks.

Finally, we tested the fragile male hypothesis of intrauterine development which indicates that male children bear much burden associated with weather shock than female counterparts. Our findings are contrary to hypothesis for HAZ and WAZ scores. Specifically, we find that female children residing in HSNP poor households and were exposed to cumulative drought observed worse HAZ scores (by 57 percentage points) than those in control sub-locations. Compared to male counterparts, we showed that female children bear a higher burden of drought, and this effect is even higher when drought is measured in cumulative terms than during in utero periods and for HAZ scores. We further show that receipt of HSNP does not seem to help households mitigate the negative effects of drought measured in cumulative terms. The finding that the male foetus is a little more resilient to weather shocks than female foetus suggests the need to support pregnant mothers. How this should be done is an area for future research input. Finally, we analysed the effect of shock using Faris cropping season approach (Faris et al., 2021). Here, evidence suggest that weather shocks occurring during land preparation and planting and harvesting periods negatively impact child health indicators while those occurring during mid season increases child health indicators. Despite the fact that our results are not statistically different from zero, they suggests differences in impacts of drought on cropping seasons. Moreover, receipt of transfer by HSNP poor beneficiary households in treated sub-locations lowers the effects of mid-season shocks by approximately 160 percentage points compared to those in control sublocation. These effects of HSNP participation on drought are high under HAZ scores compared to WAZ scores. Another important result is that, participating in HSNP transfer buffer the effects of drought experienced during mid-season period.

The results from this paper provides evidence that drought exposure negatively impacts child health, and that these effects are more pronounced during early years of a child's life. This chapter contributes to economic literature in four ways. First, it looks at effect of shocks on infant health unlike previous literature that have looked at adult outcomes. Second, our paper extends the discussion on whether social safety net can buffer the negative effects of weather shocks (Adhvaryu et al., 2019; Jessoe et al., 2018; Kim et al., 2019; Maccini & Yang, 2009). We, however, extend these studies by constructing a multi-scalar Standardized Precipitation Evapotranspiration Index (SPEI) which meets Couttenier & Soubeyran, (2014) recommendation of an alternative measure of water stress. Third, this paper speaks to the literature on shocks and consumption smoothing in village economies (Attanasio & Ríos-Rull, 2000; Cochrane, 1991; Deaton, 2003; Kochar, 1999). In this space, there seems to be no uniformity in findings (See Dercon & Krishnan, 2000; Garcia et al., 2012; Gilligan & Hoddinott, 2007; Porter, 2012). Fourth, this paper extends the discussion on the differences in gestational processes between male and female children by showing drought exposure have a large and significantly effect on male compared to female children (See Clark, D'Ambrosio, & Rohde, 2019). Finally, our paper contributes to the literature linking social safety net to climate change mitigation strategies in poor economies (Ajefu & Abiona, 2019; Asfaw & Davis, 2018; Dasgupta, 2017; Lawlor et al., 2017).

The second paper answer one question: Does receiving a public transfer crowd out or crowd in informal transfer received by rural households? This paper provides conclusive evidence that receipt of social benefits by HSNP poor beneficiary households in treated sub-location reduces the likelihood of a household receiving a cash and non-cash transfer by approximately 6 percentage points compared to households in control sub-locations. Although this result is not statistically significant at conventional levels (i.e., $P<0.1$), it corresponds to approximately 15 percent reduction relative to the baseline mean. Including the non-poor, non-beneficiary households in the analysis and imposing sub-location level effects, we observe that households in HSNP beneficiary villages have a reduced likelihood of receing cash and non-cash transfer by between 2 and 5 ppt, respectively. The 2ppt reduction in cash transfer received corresponds to about 6 percent reduction compared to the baseline mean.

Second, we find evidence that receiving public transfers (proxied by receipt of HSNP transfer) significantly reduce the amount of private transfer received by about 56 percent compared to baseline mean of private transfer received, a result that reinforces early findings on the interaction between private and public transfers in poor households. Especially, we identify crowding-out effects for the receipt of non-cash transfers but not for cash transfers. Our estimate of the per Kenyan Shilling crowding-out effect ranges between 0.73 and 0.81 for the recipt of non-cash transfers at the household and village levels, respectively. Third, we analysed the effect of HSNP in presence of drought. We show that HSNP poor beneficiary households who experienced drought (at baseline) were about 20 ppt less likely to receive non-cash transfers compared to those who have not been exposed to drought and reside in control sub-locations. Additionally, these drought exposed households are 9 ppt more likely to receive in-kind donations from other households not exposed to drought.

Finally, participation in a public transfer programme does not seem to reduce labour market participation and this has been confirmed by our various robustness tests. These findings have important implications for the design of and efficacy of social programs. In that, they offer support for the existence of strong relationship (of income sharings) amongst rural poor households. This means that evaluations of social transfers should take into account these spillover effects to avoid overstating the distributional impacts of these programs. Finally, we find suggestive evidence that HSNP poor beneficiary households in treated sub-locations favour food over other household expenditures (like education and health) compared to those in control sub-locations.

Our paper makes four additions to the economic literature. First, it contributes to the understanding of the determinants of private transfers received by households in rural Sub-Saharan Africa (SSA) (Cox et al., 2004; Cox & Jimenez, 1992; Jensen, 2004). The second contribution is in the analysis of the behavioural implication of receiving public transfer on demographic compositions and characteristics of rural households (Gerardi & Tsai, 2014; Jensen, 2004; Juarez, 2009; Koh & Yang, 2019). Third, our paper extends the discussion around consumption smoothing to support risk pooling (Morduch, 1995; Fafchamps, Udry, & Czukas, 1998). Previous literature (See Rosenzweig, 1988; Rosenzweig & Stark, 1989; Lucas & Stark, 1985) have shown that receipt of private transfers helps poor households offset income fluctuations and long distance networks through marriages, and asset holdings (like livestock) are important determinants of amount of private transfer received. Finally, we contribute to the economic literature by providing evidence of crowding out effects from a developing country perspective (See Case & Deaton, 1998; Hoddinott, 1992; Jensen, 2004; Juarez, 2009; Kazianga, 2006; Strobbe & Miller, 2011; Strupat & Klohn, 2018; McKernan et al, 2005; Nikolov & Bonci, 2020 for detailed discussion) where such information is hard to find but necessary in helping design policies that account for the socio-economic features of the rural poor in Africa. Our paper confirms crowding out effects for non-cash but not cash transfers received by poor households in the selected districts in Kenya.

The last paper analyses the effects of income on consumption of nutrients. This chapter is motivated by the fact that previous studies have failed to capture indirect effects of social programs and that may bias conclusions drawn from such analysis. However, in village economies where risk-sharing practices between communities are strong (see Townsend, 1995; Fafchamps and Lund, 2003; Dercon, et al., 2012), the effects of social programs can also accrue to non-poor, non-beneficiary households through familial or community-based channels, and this has a significant effect on the design of policies aimed at reducing extreme poverty and enhancing nutritional uptakes in developing countries. Our assessment revealed that participation in HSNP for poor beneficiary households in treated sub-locations resulted in an increase of approximately 96, 61 and 51 percent in the consumption of vitamins A, C and beta carotene compared to those in the control sub-locations. Another important findings is that HSNP non-poor, non-beneficiary households in treated sub-locations tend to consume foods rich in vitamins and minerals compared to those in control sub-locations. Specifically, we show that HSNP non-poor, non-beneficiary households residing in treted sub-locations increase (by about 70 percent) the consumption of foods rich in vitamin A compared to those in control sub-locations. This result is statisticmally significant at conventional levels. In general, the low or no impact of the HSNP on macro-nutrient consumption is not surprising and is in line with previous studies using similar datasets. For example, Merttens et al. (2013) found that the HSNP had no impact on child growth nutrients. This finding of no impact was also confirmed by Dietrich and Shmerzeck (2020). At the same time, we observe that HSNP poor beneficiary and non-poor, non-beneficiary households tend to consume more (by up to 26 percent) non-heme iron dense foods than households in control sub-locations. On targeting, our result shows that HSNP poor beneficiary households selected via CBT and DR targeting methods in treated sub-locations had diets richer in micronutrients (especially food folate) and vitamins (A and C) than those selected through social pension targeting.

Moreover, we show that HSNP poor beneficiary households in treated sub-locations consume more foods rich in minerals compared to those in control sub-locations when they are exposed to drought. Specifically, HSNP poor beneficiary households in treated sub-locations increase (by about 144 percentage points) their consumption of foods rich in beta carotene during drought compared to those in control sub-location when exposed to drought. This result is significant at conventional levels. At the same time, HSNP poor beneficiary households in treated sub-locations tend to consume less (by up to 212 percentage points) non-heme iron dense foods than HSNP households in control sub-locations. In addition, we find evidence that HSNP poor beneficiary households in treated sub-locations reduced their consumption of fatty dense and riboflavin rich foods by 40 and 91 percentage points, respectively compared to households in control sub-locations. These findings are consistent with the hypothesis that during a drought, agricultural households tend to consume cereal-based foods, which can be stored for a long time.

Finally, we shows that HSNP poor beneficiary households in treated sub-locations almost doubled their consumption of vitamin A rich foods as a result of receiving HSNP transfer, compared to households in control sub-locations. Finally, we observe that HSNP poor beneficiary households in treated sub-locations sourced most of their nutrients, vitamins and minerals (especially heme iron, vitamin A and beta carotene) from the market. Foods sourced from the market tend to be either refined, processed and/or fortified with nutrients like iron, vitamin D and calcium. In line with these findings, our paper makes four additions to the economic literature. First, it contributes to the discussion on nutrient-income elasticity from a developing country perspective, where research is still limited (Caldés et al., 2006; Dietrich & Schmerzeck, 2020a; Gertler, 2004; Haushofer & Shapiro, 2018; Jha et al., 2011; Leroy, Gadsden, Rodríguez-Ramírez, & De Cossío, 2010). Second, our study adds to the literature on the effectiveness of government aid in improving household nutrition (Hoddinott, and Skoufias 2004; Angelucci and De Giorgi 2009). Finally, our study extends the discussion on consumption smoothing (Dercon and Krishnan 2000) and risk-sharing models (Udry, 1995) from low income country's perspective.

5.2. Areas for further research

First, our analysis can be thought of as a short term impacts of a social safety net on different outcome variables. This means that it cannot answer questions concerning the medium and or long-term impacts of social safety nets on different outcome variables. In line with this, we recommend further research using long datasets (i.e., datasets collected over at least five waves) to derive long and short term effects of cash transfer. In this way, it is possible to provide a complete picture of the effect of a social programme like cash transfer that can helpful to government and other development partners. Secondly, we have relied on two strong assumptions: 1) that the effect of social transfer programme would spillover to HSNP non-poor, non-beneficiary households in treated sub-locations and 2) there is no sharing of HSNP transfer received between households in treated and control sub-locations to derive sub-locational effects. This is because we lack data on the sources of income to HSNP poor and non-poor households and we cannot observe which household is sharing what with which household. Future work remains in using datasets where sources of household income are captured, i.e., where data is clear on which households are sharing what and which households are giving out transfers. Using such detailed datasets might facilitate studies of how households are interconnected in village economies.

Another area for fruitful extension would be to use administrative instead of self reported data. This is because self reorted data are subject to misreporting bias. For instance, our study makes use self reported information as outcome variable (i.e., the amount of private transfer received or given to other households) to test crowding out effects of private transfer by public transfers. In a population where majority of the population are illiterate and poor, self reported information might not be accurate. This might have an implication on the final results obtained. Although, we have done numerous robustness checks that have shown limited effect of self-reported information on our result, future studies should use administrative data (especially those obtained from *MPESA*[114] financial statement) that capture specific amount of private transfer received or given to other households. Results from such analysis should be compared with self-reported estimates used in this study. Finally, future work should get information concerning pre-transfer income of rural households. Using pre-transfer income sources will allow estimation of non-inear models similar to those used by Cox et al., (1987).

A fourth area for future research would be to use panel instead of crossectional datasets. This is because cross sectional datasets do not capture time dimesion aspect common in panel datasets. We therefore recommend undertaking simillar analysis using panel datasets. A fourth area for future work remains in constructing drought exposure variable. In this study, we have calculated our drought indicator covering 12 months intevral to mimic local agricultural season. However, its hard to detect short periods of drought when 12 months interval is applied. We recomnd future studies should calculate SPEI using three or six months period to capture small variation in weather patterns and compared results of such studies with our findings.

A final area for future work is to undertake same studies using countrywide datasets that cover all children in all regions. This should allow researchers to make general recommendations to

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[114] This is a mobile money transfer platform being used in Kenya. It is promoted by telecommunication company called SAFARICOM Kenya.

the governments. Moreover, furute work should analyse the effect of other natural calamities like flood which are more relevant in low income countries.

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