Prenatal health and weather-related shocks under social safety net policy in Kenya

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Abstract

Exposure to weather shocks around the time of birth has been shown to have deleterious effects on later life outcomes. In the short run, such shocks can lead to income loss, especially when households are not insured but rely heavily on rainfed agricultural activities. In the long run, however, they can cause a reduction in adult earnings, human capital development and health outcomes. Despite these findings, there are few studies examining the extent to which receiving a cash transfer can help buffer the effects of weather shocks experienced early in life, especially in Sub-Saharan Africa. We close this gap in research and use a randomized control trial dataset from Hunger Safety Net Programme (HSNP) in Northern Kenya and apply regression models to estimate the effect sizes. We find that weather shocks experienced early in life reduce a child's height for age (HA) and weight for age (WA) Z- scores by 0.78 and 0.09 standard deviation respectively, controlling for other covariates. Moreover, we show that receiving a cash transfer buffers the negative effects of weather shocks. Specifically, receiving a cash transfer reduces exposure to weather shock by about 0.29 standard deviations under HA Z-scores when drought is measured in cumulative terms. However, we do not observe any buffering effect of receiving cash transfer on child health indicators when drought is measured during *in-utero* period. The paper also tested fragile male hypothesis where adverse weather shocks are expected to affect male children more than they would to females. Our results suggest that adverse weather events are worse for male children, exacerbating the male-female differences in presence of weather shocks.

JEL classification: I15, Q54, Q56

Key words: Weather shocks, Hunger Safety Net Program, Regression Model, Z- scores, Fragile male hypothesis

1 Background and motivation

Extreme weather events and climate change linked disasters cause huge economic losses to communities. Around the world, approximately USD 144 bil-

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lion was lost due to extreme weather events in 2017[1] (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[2]. 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, 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)[3] to each beneficiary household every two months[4]. The amount is equivalent to 75 percent of the World Food Program food aid ratio which was operating in the

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[1] Approximately 63.7 percent of these losses are due to hurricanes especially Harvey, Maria and Irma.

[2] In Sub-Saharan Africa 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).

[3] USD 1 = KES 103.8 (Exchange rate as at September 2019)

[4] 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

region in 2006. During the first phase of its operation (2009-2012), the program targeted 60,000 households in 48 sublocations[5] in the four districts of Kenya (Merttens et al., 2013). We examine the effect of drought on child health and malnutrition and ask whether HSNP can promote recovery of disadvantaged children.

We focus on malnutrition for at least three reasons. First, evidences have shown that malnutrition has long lasting negative implications on health, especially among children and female groups (Alderman, Hoddinott and 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) increases healthcare costs, which in turn promote poverty and inequality. Second, despite some progress observed in some countries (See Table 1), the burden of malnutrition is still unacceptably high. Finally, malnutrition increases socio-economic losses and lowers Gross Domestic Product (GDP) of a 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 child health by approximately 6 percentage points. Comparatively, exposure to cumulative drought (between and including 0-5 years) had a similar but weaker effect on height for age z-scores. Second, we find possibility of remediation for drought experienced during *in-utero* period through investments only for WAZ scores but not when drought is measured in cumulative terms (total number of droughts occurring between 0-5 years of a child's life). 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 male children are more affected by early life shocks, especially drought, than their female 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 mothers pregnant with male children. Also, it is

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[5] A sub-location is the smallest administrative unit consisting of about 200 households living close to each other. We interchangeably refer to them as villages.

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, 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). 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, Fenske, & Nyshadham, 2019; Maccini & Yang, 2009) or extreme temperatures (Jessoe, Manning, & Taylor, 2018; Kim, Lee, & Rossin-Slater, 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 (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 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 for discussion). 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 eligible for this fund if they experience severe or extreme drought.[6] Specifically, when Vegetation Condition Index (VCI) indicates severe (extreme) condition, HSNP scales

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[6] 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.

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[7]. 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 sublocations 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.[8] 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 sublocations (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.

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 1 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.

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[7] 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.

[8] 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.

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.

In Kenya, the situation of malnutrition is not different. For example, over 26 percent 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 under-nutrition. 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. This 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. The application of social safety net policies requires good theoretical and empirical grounding to guide its implementation, but this is currently missing in Africa.

4 Data

4.1 HSNP data

Our data for this study is from two sources: the Hunger Safety Net Program survey[9] collected in 2012 and weather data covering 1976-2012 from University

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[9] Source: *http://microdata.worldbank.org/index.php/catalog/1917*

of Delaware Centre for Climatic Research.[10] 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[11] (KNBS & ICF Macro, 2010). There are serious cases of stunting which affect over 30.2% of children (Table 3). Most households are income poor[12] 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 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 the data 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 treated or control sublocations. 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. We assumed that all households in treated sublocations or villages received transfer.

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 sublocations but not in control villages. For households in control villages, the number of months of exposure to the

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[10] Source: *https://www.esrl.noaa.gov/psd/data/gridded/data.UDel_AirT_Precip.html*

[11] 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).

[12] The monthly average income of households in HSNP villages (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).

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 sublocations 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.

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 3 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 4 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 sublocation 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).[13] 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, Nolan, & Kleist, 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. 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 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 sublocations into HSNP participation over the 12 months period. At every period, two sublocations (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.

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

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

life (Alderman, Hoddinott, & Kinsey, 2006; 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).

$$H_t = f\left(H_0; N_1...N_t; X; C_0, C_1...C_t; D_0, D_1...D_t; HSNP_t\right) \tag{1}$$

In this function (Equation 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 ($N_1...N_t$); history of health infrastructure available in the community ($C_0, C_1...C_t$); 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 ($D_0, D_1...D_t$). 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 ($HSNP_t$). 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 2).

$$H_0 = k\left(G, R_0, C_0, D_0\right) \tag{2}$$

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 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 0.78 and 0.09 standard deviation respectively, controlling for other covariates. We also show that receiving transfer helps household buffer the negative effects of weather shocks. Specifically, receiving a transfer reduces exposure to weather shock by about 0.29 standard deviations under HA Z-scores when drought is measured in cumulative terms. We do not, however, observe any buffering effect of receiving cash transfers on child health indicators when drought is measured during the *in-utero* period.

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 − 3, below.

$$H_{ihj} = \alpha + \beta X_i + \delta_2 D_j + \delta_3 HSNP_{hj} + \delta_4 \left(HSNP_{hj} * D_j\right) + \varepsilon_{ih} \qquad (3)$$

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. We follow the literature and use HAZ as an objective measure of long run chronic malnutrition for children (under 5 years), 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 ε_{ihj} is a zero mean error term. 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. 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 or wasting. 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, underweight and wasting separately, we ran specifications where stunting, underweight or wasting 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 being stunted or not. 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. X_i are covariates like monthly household consumption expenditures, access to clean water services, access to improved toilet, age of the child, ownership of female cattle, goats and camels, and household size measured in Organization for Economic Cooperation and Development (OECD) terms. 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 2) HSNP operated in moderately dry areas (SPEI =-1.08) 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.

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.

7.1 Sample demographic characteristics

We first run a student t-test on important variables in our study (Table 2). 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, its 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 preceeded 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 nurtitient deficiencies has also been argued by Dietrich & Schmerzeck, (2019).

We find that HSNP districts were on average, moderately dry: SPEI of -0.853 (Table 2). 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 of birth, children were exposed to between 0 and 4 droughts from *in-utero* to age 5 (and including age 5).

Households had low on-farm income of about 12,759 Kenya Shillings (about USD 128) per annuum (Table 2). 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 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 households 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, 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.

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 3 below presents the result of these regressions.

One key result (in Table 3) is that the effects of cumulative drought exposure on household resources and expenditure are robust under all drought conditions: the in uterine period and cumulative drought exposure. We find that a unit increase in cumulative drought exposure, measured between 0-5 years, increases monthly household total consumption expenditure (in nominal terms) by about 4 to 7.5 percentage points, 24 months after the launch of HSNP in Kenya. This increase in total monthly household consumption expenditure is statistically significant at one percent significance level depicting the high impact a drought has on household consumption expenditure patterns. Here, our finding mirror 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. We find in addition that being exposed to HSNP increased household food expenditure by 8.6 percentage points. This increase in consumption expenditure is partly financed by private transfers received by households. We observed for instance, higher amounts of food aid and supplementary feeding programs received by HSNP households[14] in the three months preceeding the survey. In addition, households reported receiving cash transfers, non-cash transfers and donations from religious organizations and development partners. We suspect that these increases in expenditure might be financed by livestock sales, a common form of savings often encountered in HSNP districts in Kenya. However,

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[14] 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.

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 and healthcare but not to non-food items. Specifically, we show that poor households indeed increase their budget share for food and healthcare by approximately 92 and 0.3 percent respectively. These findings are statistically significant at 5 percent level and they indicate the important share these items make in the basket of poor households.

Interestingly, however, we find that households strongly reduce their expenditure share allocation towards non-food items (when drought is measured during in-utero period), thus confirming our *a priori* hypothesis that assumes that households increase their investment towards their children's health during drought. Here, our results are consistent with Bobonis (Bobonis, 2009) who showed that *PROGRESSA*[15] 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 cumulative drought exposure between 0-5 years is responsible for a reduction in household farm income by 6.4 percent 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 children's 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 and Davis, 2018; Maccini and 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 significantly increases household health expenditure by 0.5 percentage points. This result is consistent even if health expenditure is measured as a share of total household expenditure and is significant at one percent significant level in all health expenditure measures. This 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.

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[15] 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 (0-5years) and lactating women attend nutritional clinics and finally, pregnant women must attend clinics. These transfers were given to mothers only.

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 3, column 4) show that exposure to drought during this critical window increases investment in child health on average. 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 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 drought during in utero than when drought is measured in cumulative terms. Specifically, households reduce their expenditure on non-food items by approximately 12 percentage points, and this result is strongly significant at one percent. This reduction in expenditure is captured by mainly food consumption expenditure: higher expenditure shares on food when drought is measured during in utero than when it is measured in cumulative terms.

7.3 Effect of early life drought on child health

We present the result of our main regression (equation 1) on the effect of drought exposure on child health indicators (HAZ and WAZ scores) 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 4 presents the results of our regressions. Our variables of interests (in Tables 4 and 5) 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 or in cumulative terms) 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.

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) and Weight for Age Z (WAZ) scores. We found that a unit increase in cumulative drought exposure decreased HAZ and WAZ scores by between 0.60-0.65 and 0.07-0.14 standard deviation, respectively. Our results mirror those of Dasgupta, (2017) who found that exposure to cumulative drought reduced child WAZ and HAZ scores in India by 0.06 and 0.98 standard deviation respectively. 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 suggestive evidence of the buffering effect of HSNP transfer on cumulative drought exposure for HAZ and WAZ scores. Although our coefficients are not significant, 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. Under WAZ as a dependent variable, we find coefficients which are negative and not significant, depicting no buffering effect of social safety net transfer on WAZ scores. We also find that access to supplementary feeding reduced HAZ scores by about 0.34 standard deviation (result not reported here but available upon request). We also observe that ownership of animals (female goat and camel) reduces HAZ scores. This relation reflects the fact that ownership of assets like female cattle helps households access milk which, if consumed, can mitigate the effect of weather shock.

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 robustness check, we estimate the above equation 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 5) and confirm the negative effect of drought exposure on HAZ and WAZ scores. The estimates on our measure of drought exposure are relatively high compared to those reported under cumulative drought exposure when participation is capture in terms of months of exposure. These results speak 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 statistically significant effect of the interaction between exposure to drought and receipt of HSNP transfer on WAZ 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.

Children in treated households reported slightly better health indicators (HAZ, WAZ scores) compared to those in control households (Table 2). Instead, we observe that children who were exposed to drought and in HSNP treated households experienced worse WAZ scores than 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 might be 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. We suspect that the effect of HSNP transfer might be neutralized by the effect of Ramadan observance among Muslim families.

Turning on to other covariates, we find that household consumption expenditure reduced HAZ scores but increased short term child health indicators like WAZ scores. We observe that environmental factors such as access to improved water source, improved toilets and type of flour reduce short term child health indicators: WAZ scores. 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 mixed result concerning ownership of female animals. 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.

7.4 Estimation of prevalence of stunting, wasting and underweight

We also analysed our results using stunting, wasting 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 6.

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 6. 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.

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 6 presents results for average stunting, underweight and wasting respectively with a cumulative measure of drought. 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 but decreases the probability of wasting. Specifically, we find that exposure to drought increases probability of stunting by 9.5 percent. 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 significant 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 1). Our result showed that stunting would have been biased downwards by almost 5.9 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 nonlinear 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). Children who were exposed to drought during the earlier years of their life experienced worse HAZ scores by 0.02 standard deviation and this coefficient is statistically significant at one percent.

These children can recover from such weather shocks when they receive cash transfer through HSNP transfer. We also observe a negative and statistically significant effect of receiving HSNP transfer on HAZ 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 our a priori assumption: cash transfer would help smallholder households cushion the negative effects of malnutrition.

Turning to covariates, we observe that children born in Marsabit and Wajir experienced a reduction in child health with WAZ scores recording the highest level of reduction. An additional result is that access to improved toilets had an opposite but statistically significant sign on the coefficient. 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.

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 above separately (with HAZ and WAZ as outcome variables) using gender disaggregation. We varied our measurement of drought measure 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 7 presents the result of our analysis.

Our result confirms the fragile male hypothesis for HAZ and WAZ under different drought scenarios. In all the models (HAZ and WAZ), we provide a qualified support that male children bear more burden than female counterparts. The coefficients on drought exposure under male children is approximately -0.7 for HAZ scores and -0.3 for WAZ scores. We find greater effect of drought on male children health outcomes *in-utero* than when drought is measured in cumulative terms. Being exposed to drought during *in-utero* reduces both HAZ and WAZ scores of male children by between 0.7 and 0.3 standard deviations respectively compared to female children. The fragile male hypothesis, however, seems not to hold for WAZ scores in all model specifications (Result not presented here but available upon request). Under WAZ scores, we find that exposure to cumulative drought (0-5 years) increases WAZ scores for female children by 0.6 standard deviations. The effect is positive and statistically significant at five percent level.

Nevertheless, we observe that when drought is measured during the *in-utero* period, 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 WAZ scores than male counterparts although the coefficients are not significant. It is interesting to note that when 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.

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 8) show in general that the coefficient on male and female children is reduced by over 0.3 standard deviations for HAZ scores and 0.2 standard deviations under WAZ scores.

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 male children's health. This means that women who are pregnant with male children require more attention and support during this critical period than those pregnant with female children. 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, although more resistant to male children, female children are also vulnerable to early life shocks with the highest effect observed when drought is measured in cumulative terms. This means that nutritional intervention should not only target male children, but female children should also be targeted. Such a policy might help improve the conditions for all children.

Our findings that show that male children suffer higher 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.

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, wasted or underweight. We established that exposure to drought (measured either in cumulative terms or as a dummy during in utero period) increases household total consumption expenditures, food and health expenditures (in nominal terms) but reduces non-food consumption expenditures (in nominal terms) and annual farm income levels. This result 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 drought exposure during the *in-utero* period has much higher effect than cumulative drought effects and this speaks 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 have higher returns than those undertaken in later periods of life. In addition, we provide evidence that confirms that exposure to drought worsens child HAZ and WAZ scores. We did not find any evidence that shows that receiving HSNP transfer buffers the effects of drought on child nutrition.

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 confirm this hypothesis for HAZ and WAZ scores. We showed that male children bear a higher burden of drought, and this effect is even higher when drought is measured in cumulative terms and for HAZ scores. The finding that the female foetus is a little more resilient to weather shocks than male foetus suggests the need to support pregnant mothers of male children. How this should be done is an area for future research input.

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.

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Table 1: Prevalence of stunting in Africa (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)

Table 2: 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)
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; 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, N=677; Control households, N=659; Full sample,* ***N=1,336***

Source: HSNP data

Table 3: Effect of drought on child health inputs

Variables	Household comparison (1) HSNP households	(2) Non-HSNP households	Drought shocks (3) Drought (0-5 years)	(4) Drought *in-utero* (Dummy)
A: **Household resources (Kenya Shillings)**				
Total expenditure	12100.56***	10923.59***	0.075***	0.042*
	(216.75)	(176.74)	(0.015)	(0.023)
Farm income	11585.91**	13964.98**	-0.064	-0.634*
	(632.23)	(693.75)	(0.237)	(0.349)
Food expenditure	9400.98***	8761.33***	0.086***	0.075***
	(149.56)	(138.26)	(0.015)	(0.023)
Non-food expenditure	2274.29***	1815.15***	-0.002	-0.118***
	(71.24)	(54.45)	(0.030)	(0.040)
Health expenditure	194.52**	148.06**	0.502***	0.362**
	(13.18)	(14.36)	(0.098)	(0.143)
B: Consumption expenditure and farm income shares (%)				
Food share	0.79***	0.82***	0.914**	2.534***
	(0.003)	(0.003)	(0.383)	(0.534)
Non-food share	0.18***	0.16***	-0.010***	-0.023***
	(0.003)	(0.003)	(0.003)	(0.004)
Health share	0.02**	0.01**	0.003**	0.002
	(0.001)	(0.001)	(0.001)	(0.002)
Farm income share	0.39	0.41	-0.013	-0.047
	(0.02)	(0.018)	(0.013)	(0.030)

Note: *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 (clustered at household level) in parentheses; 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 (years) of a child, gender of child;* ***N=1,336***.

Table 4: Estimating the effect of drought on child health using OLS

	(1)	**(2)**	**(1)**	**(2)**
Variables	**HAZ**		**WAZ**	
Cumulative drought (0-5 years)	-0.66***	-0.65***	-0.14	-0.07
	(0.16)	(0.17)	(0.09)	(0.09)
HSNP (Dummy, 1=Treated)	-0.14		-0.14	
	(0.33)		(0.17)	
HSNP exposure (Months)		-0.01		0.006
		(0.03)		(0.02)
HSNP exposure X Drought		**0.03**		**-0.002**
		(0.02)		**(0.01)**
HSNP X Cumulative drought	**0.029**		**0.009**	
	(0.018)		**(0.010)**	
Constant	4.46**	4.48**	-2.05**	-2.02**
	(1.74)	(1.75)	(0.98)	(0.98)
R-squared	**0.08**	**0.08**	**0.06**	**0.06**
Controls	**Yes**	**Yes**	**Yes**	**Yes**

Note: *Dependent variables are HAZ and WAZ scores. Robust standard errors (clustered at household level) in parentheses; 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; all regressions include ownership of female cattle, camel and goats, access to improved toilet and water source, log of monthly household consumption expenditure, days a household is food insecure in the last 30 days, age (years) and age (years) squared but not reported here; N=1336*

Table 5: Estimating the effect of drought on child health

	(1)	**(2)**	**(1)**	**(2)**
Variables	**HAZ**		**WAZ**	
Drought in utero (Dummy)	-0.61**	-0.68***	-0.22	-0.26*
	(0.27)	(0.26)	(0.14)	(0.14)
HSNP (Dummy, 1=Treated)	0.34**		0.09	
	(0.17)		(0.09)	
HSNP Exposure (Months)		**0.03***		**0.01**
		(0.02)		**(0.01)**
HSNP X Drought in utero	**-0.300**		**-0.39****	
	(0.374)		**(0.19)**	
HSNP Exposure X Drought in utero		-0.01		-0.03*
		(0.03)		(0.02)
Constant	5.957***	5.91***	-1.66*	-1.65*
	(1.758)	(1.76)	(0.97)	(0.97)
R-squared	**0.08**	**0.08**	**0.07**	**0.07**
Controls	**Yes**	**Yes**	**Yes**	**Yes**

Note; *Dependent variables are HAZ and WAZ scores; Robust standard errors (clustered at household level) in parentheses; 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, days a household is food insecure in last 30 days, age (years) and age (years) squared but not reported here;* ***N=1336.***

Table 6: Effect of cumulative drought on child health using binary models

	Stunting		Underweight	
Variables	(1) Probit	(2) loglog	(1) Probit	(2) loglog
Cumulative drought (0-5 years)	0.095***	0.42***	0.02	0.09
	(0.03)	(0.12)	(0.03)	(0.13)
HSNP (Dummy, 1= Treated)	0.03	0.17	0.08	0.35
	(0.05)	(0.23)	(0.06)	(0.24)
HSNP X Cumulated drought	-0.07*	-0.29*	-0.05	-0.19
	(0.04)	(0.15)	(0.04)	(0.16)
Constant		-4.95***		-1.72
		(1.26)		(1.31)
Controls	Yes	Yes	Yes	Yes

Note: *Dependent variables = Stunting, Underweight and Wasting;* Marginal effects are evaluated at sample means; *Robust standard errors (clustered at household level) in parentheses; 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; loglog is complementary log-log regression;* ***N=1,336***

Table 7: 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)	**-0.72*****	**-0.59****	**-0.31*****	**0.08**
	(0.21)	**(0.25)**	**(0.10)**	**(0.14)**
HSNP (Dummy, 1= Treated)	-0.02	-0.29	-0.27	0.004
	(0.43)	(0.48)	(0.22)	(0.24)
HSNP X Cumulative drought (0-5 years)	0.03	0.03	0.03**	-0.01
	(0.02)	(0.03)	(0.01)	(0.01)
Panel B: Drought measured during *in-utero* period (Dummy)				
Drought in utero (dummy)	**-0.79****	**-0.44**	**-0.37****	**-0.11**
	(0.36)	**(0.39)**	**(0.18)**	**(0.21)**
HSNP (Dummy, 1= Treated)	0.43	0.26	0.18	-0.02
	(0.22)	(0.25)	(0.12)	(0.13)
HSNP X Drought in utero (Dummy)	-0.35	-0.28	-0.34	0.42
	(0.52)	(0.54)	(0.26)	(0.28)
Observations	**689**	**647**	**689**	**647**
Control	**Yes**	**Yes**	**Yes**	**Yes**

Note: *Dependent variables are HAZ and WAZ scores; robust standard errors (clustered at household 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 include ownership of cattle, camel and goats, access to improved toilets and water source, log of monthly household consumption expenditure per adult equivalence, days a household is food insecure in last 30 days, age in years but not reported here.*

Table 8: Effect of weather shock by gender category

	HAZ		WAZ	
Variables	**(1) Male**	**(2) Female**	**(1) Male**	**(2) Female**
Cumulative drought (0-2 years)	-0.49***	-0.42*	-0.18**	0.15
	(0.18)	(0.23)	(0.09)	(0.14)
HSNP (Dummy, 1= Treated)	0.27	-0.05	0.06	0.14
	(0.36)	(0.41)	(0.19)	(0.22)
HSNP X Cumulative drought (0-2 years)	0.09	0.20	0.05	-0.27
	(0.26)	(0.29)	(0.13)	(0.17)
Observations	**689**	**647**	**689**	**647**
Controls	**Yes**	**Yes**	**Yes**	**Yes**

Note: *Dependent variable- HAZ and WAZ scores; robust standard errors (clustered at household 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 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, number of days a household is food insecure in last 30 days, age (months) of child and age (months) of child squared.*

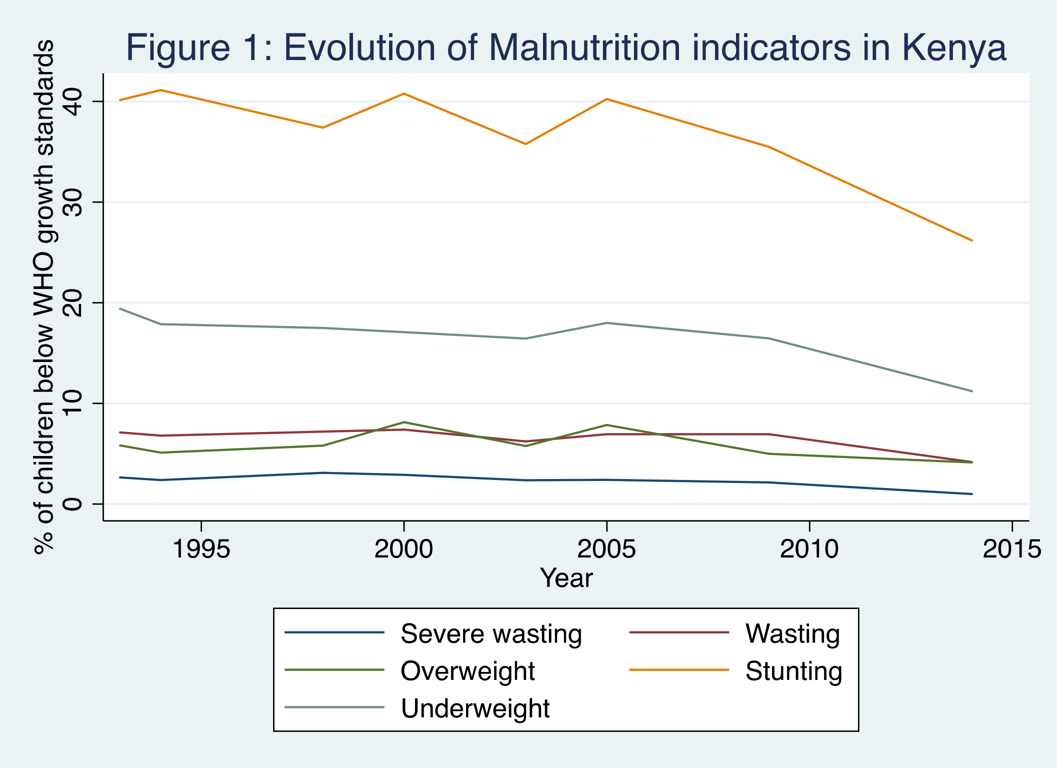


Figure 1: Evolution of Malnutrition indicators in Kenya

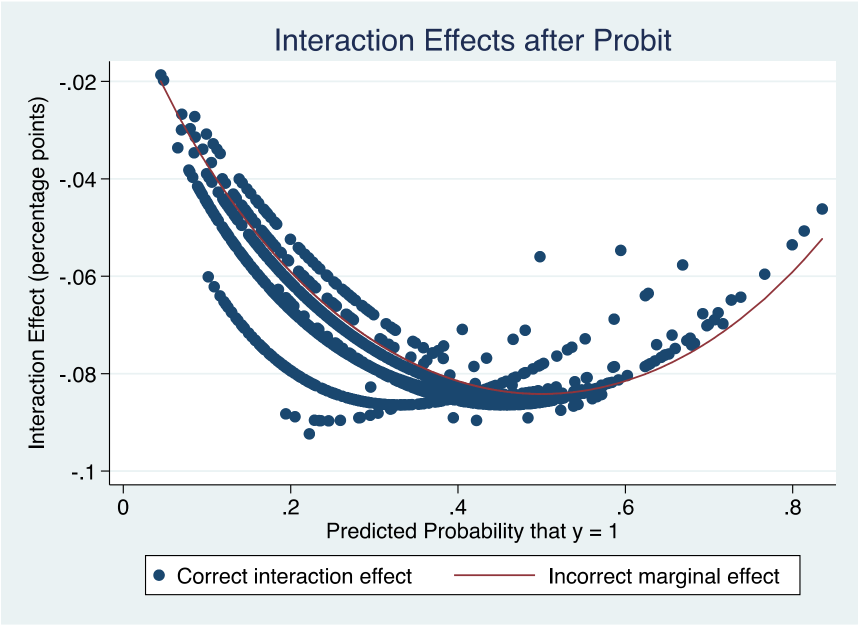
Notes: Severe wasting captures the % of children below <- 3 standard deviations from medium weight-for-height (WH) of World Health Organization (WHO) child growth standards; **Wasting and Overweight** capture the % of children below <-2 standard deviations from medium WH of WHO child growth standards; **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.

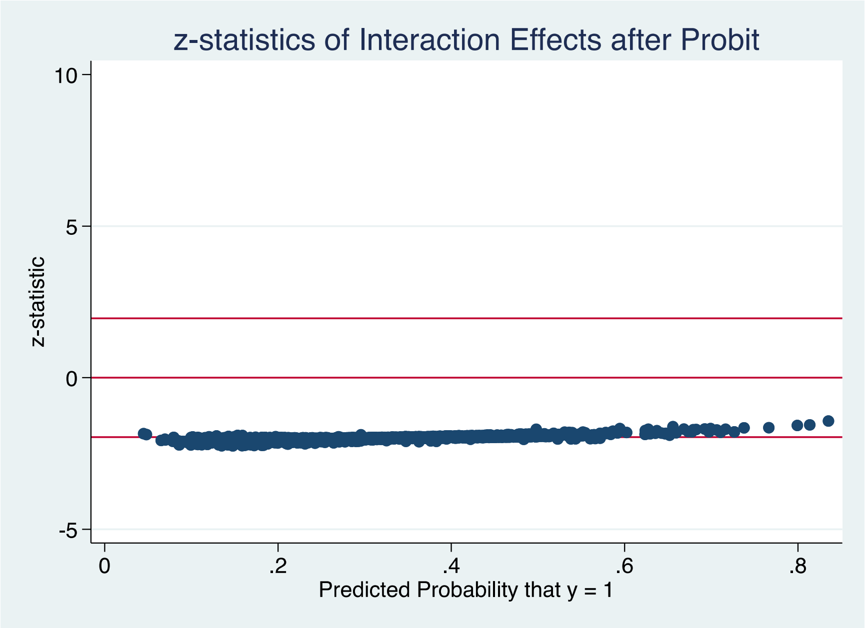
Source: UNICEF/WHO, (2019)

Appendix 1: 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 villages or otherwise.

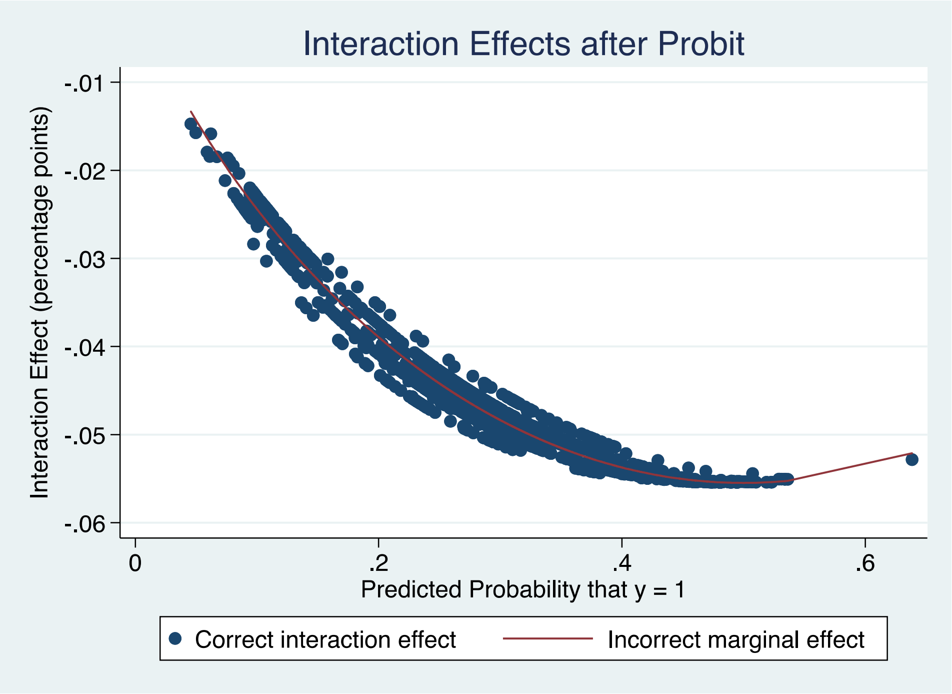
1A. HAZ dummy (1=HAZ<-2)

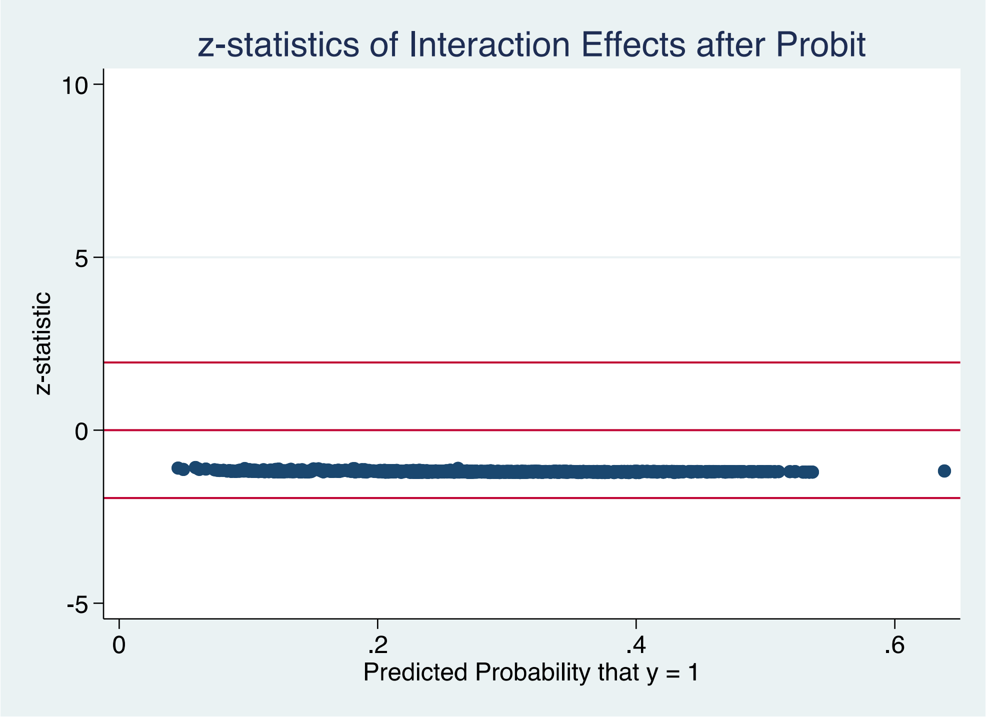




The correction result in a 5.9 percent increase in coefficient estimate to -0.0727 with a standard deviation 0.0364 compared to uncorrected marginal effect coefficients.

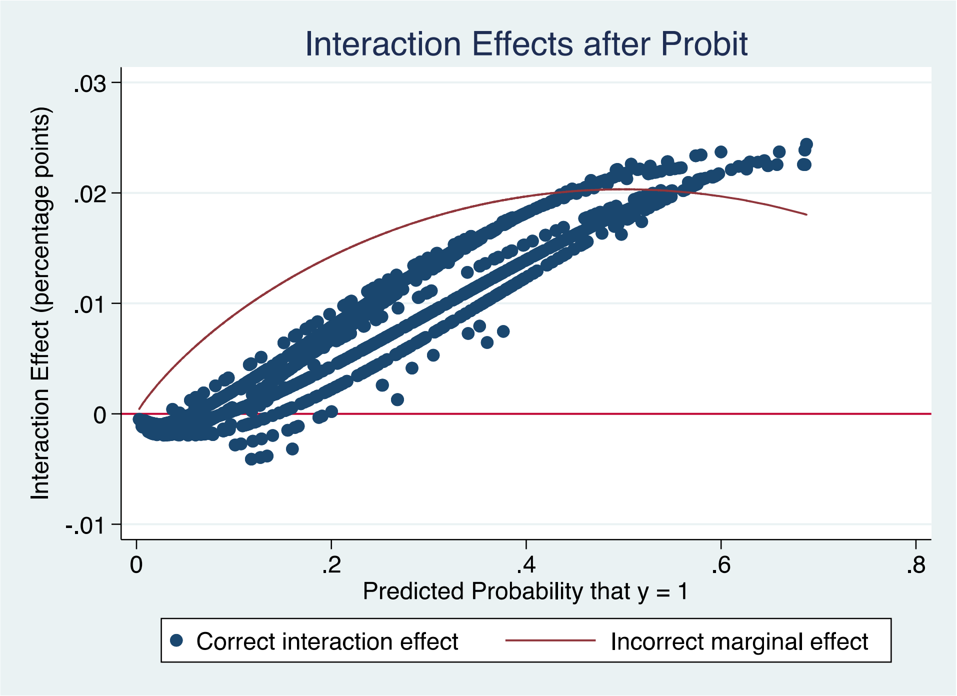
1B. WAZ dummy (1= WAZ<-2)

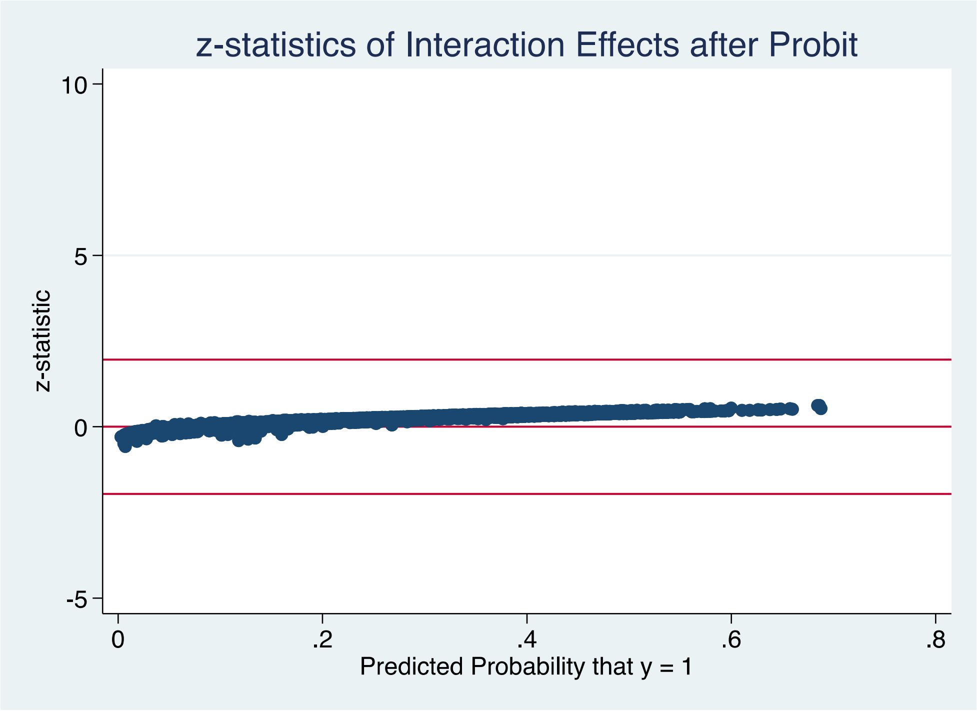




Here correcting for interaction effects does not significantly change the coefficients which stabilized at -0.0454 and a standard deviation of 0.0379. this coefficient is not significant.

1C. WHZ dummy (1=WHZ<-2)





This correction result in approximately 1.7 percent low coefficients of 0.0084 with a standard deviation of 0.033 compared to marginal effects of the same estimates. However, the estimates are not significant.

Appendix 2: Effect of drought and HSNP exposure (in months) on child health indicators using Probit model

	Stunting	Underweight	Wasting
Variables	(1)	(1)	(1)
Cumulative drought (0-5 years)	0.09***	0.014	-0.048*
	(0.03)	(0.029)	(0.026)
HSNP exposure (Number of months)	0.002	0.04	0.004
	(0.005)	(0.005)	(0.004)
HSNP exposure X Cumulated drought	-0.006	-0.003	0.001
	(0.003)	(0.004)	(0.003)
Controls	Yes	Yes	Yes

Note: *Dependent variables = Stunting, Underweight and Wasting; Robust standard errors (clustered at household level) in parentheses; 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, days a household is food insecure in last 30 days, age in years but not reported here; the coefficient on the Interaction term is the corrected for nonlinear model;* ***N=1,336.***

Appendix 3: 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 3a: Summary of drought classification scale for SPEI values

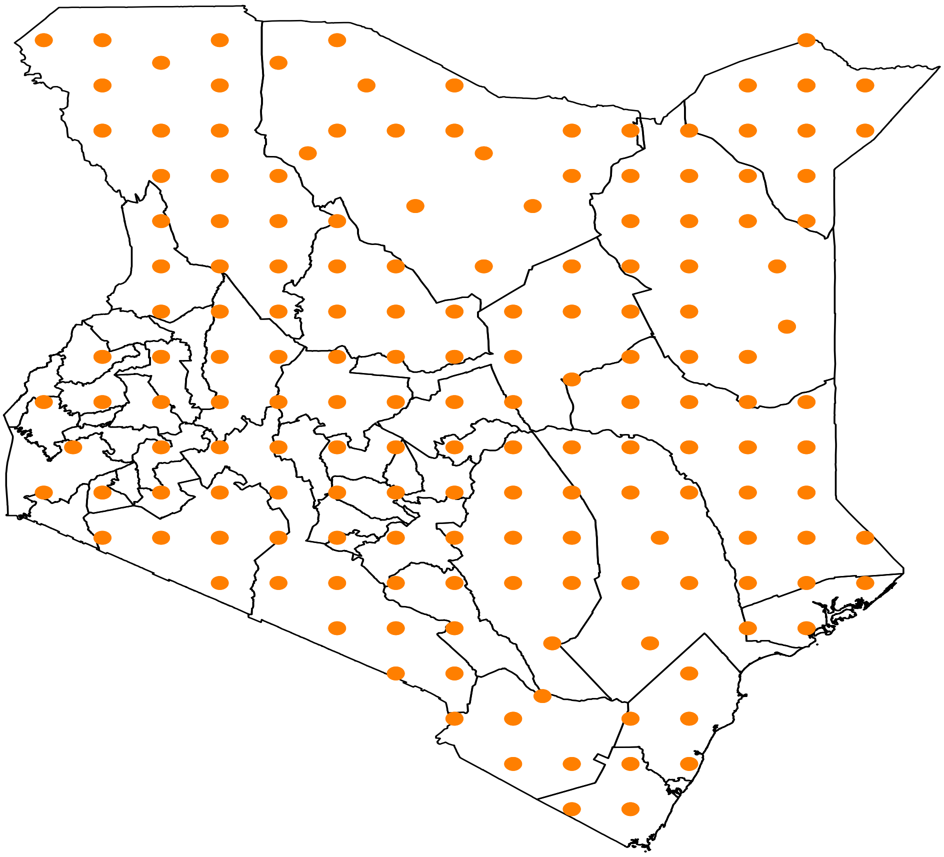
SPEI values	**Drought classification**		**Probability of drought occurrence**	**Our classification**
	(McKee et al., 1993)	(Agnew, 2000)		
Greater than 0.00	No drought	No drought		
Less than 0.00	Mild drought	No drought	0.500	No drought
Less than -0.50	Moderate drought	No drought	0.309	
Less than -0.84	Moderate drought	Moderate drought	0.201	
Less than -1.00	Moderate drought	Severe drought	0.159	
Less than -1.28	severe drought	severe drought	0.100	
Less than -1.50	severe drought	Extreme drought	0.067	Drought
Less than -1.65	Extreme drought	Extreme drought	0.050	
Less than -2.00	Extreme drought	Extreme drought	0.023	

Source: Adapted from Agnew, (2000)

Appendix 4: Spatial distribution of weather stations in Kenya (1976-2012)

In Figure 2 below, we provide spatial distribution of weather stations (in yellow dots) across Kenyan landscape with complete precipitation and temperature data covering 1976-2012 period.

Fig 2: Weather Stations with Non-missing Data, 1976-2012



Our result (Figure 2) 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.