

Sveriges lantbruksuniversitet Swedish University of Agricultural Sciences

**Department of Economics** 

# How does drought affect child health outcomes in Zimbabwe?

- An econometric analysis

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Master's thesis · 30 hec · Advanced level (A2E Environmental Economics and Management - Master's Programme Degree thesis No 1174 · ISSN 1401-4084 Uppsala 2018 How does drought effect child health outcomes in Zimbabwe? - An econometric analysis

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Credits: 30 hec Level: A2E Course title: Degree Project in Economics Course code: EX0537 Programme/Education: Environmental Economics and Management – Master's Programme Faculty: Faculty of Natural Resources and Agricultural Sciences

Place of publication: Uppsala Year of publication: 2018 Name of Series: Degree project/SLU, Department of Economics No: 1174 ISSN 1401-4084 Online publication: https://stud.epsilon.slu.se

**Key words:** Zimbabwe, Height-for-age, Drought, Standardized Precipitation Evapotranspiration Index, Human capital



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### Summary

This thesis contributes to the broader economic literature on income shocks and child health outcomes. Child health outcomes are known to be an important factor in determining the overall health, school results and productivity later on in life as an adult. The purpose of this study is to investigate the association between exposure to drought around the time of birth and child health outcomes in Zimbabwe. Drought is a relevant measure for an income shock since Zimbabwe is heavily dependent on rain-fed agriculture that provides approximately 70 percent of the population with their livelihoods. The key measure for the child health outcome is the height-for-age value, known as chronic malnutrition. Furthermore, this paper examines if a gender-bias exists as well as if residing in the rural areas could be a negative risk factor for the drought chock.

The main results indicate that moderate drought at the time of birth is associated with a negative deviations from the mean reference population's height-for-age value. Meaning that the child's growth would be negatively affected by the drought. The analysis could not establish if gender or urban versus rural status made the child more vulnerable to drought.

My findings are relevant for low-income countries with prevalent levels of malnutrition where drought could affect food security and malnutrition levels, hence affect the human capital formation.

### Abbreviations

- DHS Demographic Health Survey
- HAZ Height-for-age
- FAO Food and Agriculture Organization
- SLU Swedish University of Agricultural Sciences
- SPEI Standardized Precipitation Evapotranspiration Index
- SPI Standardized Precipitation Index
- UNICEF United Nations Children's Fund
- HDI Human development Index
- **SDG** Sustainable Development Goals
- MSD Meteorological Services Department of Zimbabwe
- **ZDHS** Zimbabwe's Demographic Health Survey
- ZIMSTAT Zimbabwe National Statistics agency
- PDSI Palmer drought severity index
- WFP World food programme

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### 1. Introduction

### 1.1 Background

Previous economic research has investigated how early-life shocks, that is any event that harms fetal, infant, or childhood health in the short term, affect the outcomes later in life as an adult (Currie and Vogl 2013). Early childhood development is well documented in economic literature as an important factor for school performance as well as future productivity and income as an adult (Young and Mundial1996). FAO supports this and states that nutrition is a fundamental condition for human welfare. They state that good nutrition represents an investment in human and social capital, and that human capital is the key determinant of a community's well-being (Wang and Taniguchi 2018).

One of the key indicators for the Sustainable Development Goal (SDG) number 2 - Zero hunger, is the reduction in chronic malnutrition, since it presents is a huge challenge to the productivity and health of a population (ACC, U., 1999). One third of all malnourished children worldwide live in Sub-Saharan Africa. Unfavorable climate and drought conditions is another factor that negatively affects food availability and production, hence affects the levels of undernutrition (Akombi et al. 2017).

Furthermore, malnutrition is viewed as one of the five largest adverse health impacts of climate change (Phalkey et al. 2015), especially since climate change is expected to increase extreme weather events which reduce cereal yields and threaten food security (Lloyd et al. 2011; Dinkelman 2017). Drought is one of Africa's most common natural disaster and drought is expected to become an increasing source of income shocks in developing countries (IPCC 2014). Given the central role of reducing malnutrition to improve the human health in developing countries, and in the light of income shocks (drought) it is of interest to understand if and how drought will affect child health outcomes.

In this paper, I examine how exposure to local drought in early-life affects children's health outcomes in Zimbabwe. Zimbabwe provides a compelling case study due to three main reasons. First, the country's population is highly dependent on rain-fed agriculture for their main source of food and income. For example, the main staple food in the country is maize, which is especially sensitive to rainfall shortages that interrupt the growing season (Le Roux 2009). Second, Zimbabwe is often affected by drought and the occurrences of drought is expected to increase in the future due to climate change. Last but not least, malnutrition in all its forms is prevalent among children all over Zimbabwe and limits their cognitive and physical growth (UNICEF). I contribute to the previous literature by using individual survey data for the whole country rather than a limited geographical area in Zimbabwe. Furthermore, I investigate the droughts in the form of a drought index and not only as insufficient rainfall.

### 1.2 Problem statement and research questions

The purpose of this study is to investigate the relation between early-life exposure to drought and child health outcomes in Zimbabwe. Other purposes are to examine the role of gender and if residing in the rural areas could be a vulnerability factor. This will be done by answering the following three research questions:

- (i) How does exposure to drought, at the time of birth, affect child health outcomes in Zimbabwe?
- (ii) How does the impact vary across gender?
- (iii) Are children in the rural areas more sensitive to early-life exposure to drought than children in urban regions?

To investigate the research questions I apply econometric analysis on survey data from the Zimbabwe Demographic Health Survey (ZDHS). I combine the ZDHS data with a drought index to capture the weather effect and investigate the child health outcome. I examine the specific research questions by using pooled-OLS estimates with fixed effects.

### 1.3 Delimitations

The scope of this theses is limited to the country of Zimbabwe between the years 1999-2015. This was the longest period that all the necessary data was available for my analysis. The data is collected in the form of survey data from the Zimbabwe Demographic Health Survey (ZDHS) and covers children under the age of five. The ZDHS only collects data for children that are alive, therefore my analysis does not take into account children that passed away before they turned 5 years old. Therefore, one weakness in the model is that it does not account for infant mortality or changes in fertility in case of a drought event. Another weakness is that the DHS data is cross-sectional in nature and my data set creates a repeated cross-sectional data set since it covers more than one year. In repeated cross-sectional data the same individuals are not followed over time and therefore it is not possible to include an individual's history in the model. I investigate the effects of drought by using the Standardized Precipitation Evapotranspiration Index (SPEI). I analyze the data using pooled-OLS with fixed effects, dynamic models are not investigated.

The aim of this study is not to provide concrete measures for policy-makers, but rather to provide a deeper understanding of the complex relationship between drought and the nutrition status among children under five years old in Zimbabwe.

### 1.4 Outline of the thesis

The remaining part of the thesis is organized as follows. Chapter number two, provides the reader with a literature review on the topic, to give a better understanding on the previous research on early-life-shocks, health outcome and the consequences for the future. The main focus is on early life chocks related to drought or insufficient rainfall. The literature review is followed by a chapter on the Zimbabwean country context since, it is important to understand the context in which my results should be interpreted.

In the fourth chapter the selected data variables and sources as well has how the data has been merged are explained in detail. Thereafter, chapter five presents my baseline equations and the econometric models that will be investigated. Chapter six summarizes my main finding and discusses the results from the previous econometric analysis. Chapter seven concludes and answers the research questions.

### 2. Literature review

Economic research has shown that inadequate rainfall or drought events have significant impacts on child health outcomes and other outcomes such as increased risk of later-life disabilities (Dinkelman 2017), lower performance in school (Alderman et al. 2006), lower growth rate (Hoddinott and Kinsey 2001) and lower earnings as an adult (Maccini and Yang 2009) to mention a few examples.

Countries are from time to time subject to exogenous shocks that result in different forms of utility losses. The severity of these damages are determined by the length and strength of these shocks and could possibly have long-term effects, especially if households are unable to smooth their consumption during the shock (Jensen 2001). Alderman et al. (2006) link the literature on exogenous shocks to the literature on child health outcomes of preschool children in Zimbabwe. They analyze how transitory shocks in terms of war and drought experienced prior to the age of three affect the child's nutritional status and education accomplishments. They analyze a long-term panel data set collected from longitudinal surveys of households and children residing in three resettlement areas of rural Zimbabwe. Their findings indicate that better-quality nutrition increased height as a young adults and lead to the completion of a greater number of years in school. These findings from Zimbabwe support the theory that early-life lack of sufficient nutrition can have long lasting effects on health outcomes as well as school results and productivity (Alderman et al. 2006).

Child health outcome is the result of a complex set of variables ranging from the source of child, mother and household demographics' to the presence of diseases among other factors (Akombi et al. 2017). The complexity of the events leading up to the outcome can therefore be a challenge to identify. However, Alderman et al 2006 argue that their research method and results are robust. Nevertheless, they highlight some concerns that could possibly question the robustness. First, they highlight that their estimates do not account for changes in fertility or birth-spacing. Second, their model does not control for birth order despite the finding by .e.g Hortson (1988) that higher-order children are more likely to have poorer nutritional status since they compete with siblings for the household's resources. There is also more competition for the mothers care and a higher risk of infection. A study from Bangladesh supports these results and find that low child birth order reduces child malnutrition (Rayhan and Khan 2006).

Hoddinott and Kinsey (2001) investigate how weather shocks affect the health outcome of children measured as growth in heights of young children 12-60 months old. Their main reason for using this outcome variable (among other reasons) is that children are especially vulnerable to chocks that lead to growth faltering, which can lead to low performances in school and in the long-run poor income and lower productivity. Furthermore, growth rates and height are good indicators of a child's underlying health status. They use household data from three rural settlements in Zimbabwe matched with rainfall data (the rainfall data defines one drought in 1995/6). The author's main finding is that young children grow more slowly in the aftermath of a drought, especially children in poor households. The drought in 1995/96 lowered the annual growth rate in the sample by 1.5-2 centimeters. Four years after the drought the children were still shorter compared to the children who were not affected by the drought. The estimates controlled for large number of children, maternal and household characteristics and the authors state that the results prove to be robust including the treatment of heteroscedasticity.

One weakness that Alderman et al. (2006) and Hoddinott and Kinsey (2001) have in common is that they do not look at children from all over Zimbabwe but are instead limited to three resettlement areas for a limited time-period. Moreover, they measure drought as average rainfall,

and do not account for local drought conditions. I extent the previous research by investigating how child health outcomes are affected by local drought. Using individual survey nationwidedata from Zimbabwe (collected from the ZDHS) to measure the child health outcome and the SPEI to define drought. For that reason my research design has been influenced Dinkelman (2017).

In light of the fact that natural disasters are projected to become more common in Africa due to climate change Dinkelman (2017) investigates the effects of droughts on long run differences in human capital measured as disability. Her research exploits a quasi-random variation in exposure to many local droughts in different districts in South Africa. The model uses data from the 1996 census report among South African homelands during apartheid and investigates later life disability rates between the districts with control variables for birth year and district. Data from the census report and drought data are merged into a sample by using district and year of birth. She argues that local rainfall is a relevant measure of an important environmental shock in South Africa since maize is the staple food in the country. Furthermore, maize yields are vulnerable to droughts or insufficient rainfall and maize is more sensitive to low levels of rainfall compared to excess of rain. The main result is that exposure to drought in early childhood (before 4 years of age) significantly raises the risk of having a severe disability later on in life. The measured effects were even larger in the sub-sample of males compared to females, suggesting a gender aspect. The research design of my paper has been inspired by Dinkelman (2017), but there are several differences between our papers. First, I focus on Zimbabwe not South Africa and my outcome variable is height-for age (chronic malnutrition) rather than later-life disability. Furthermore, Dinkelman (2017) uses the SPI as her measure of drought whereas I use the SPEI, the main advantage to the SPEI is that it takes into account the importance temperature on drought conditions unlike the SPI (a more detailed explanation of the drought variable can be found in chapter three).

Dinkelman (2017) states that her research is most close to Maccini, and Yang (2009) who investigate the long-run effects of poor rainfall, in the year of birth, of Indonesian adults. They investigate how the effect from weather around the year of birth affects the later life outcomes on health, education and socioeconomic outcomes. Their sample group consist of 4,615 women and 4,277 men born between 1953 and 1974 outside urban areas. The later-life outcomes are measured by using health outcome data from the year 2000 and rain fall data is collected from weather stations in the entire Indonesia<sup>1</sup>. Their findings suggest that women who experienced higher rainfall in the year of birth have higher education, are taller, wealthier and report higher scores on self-reported health. The authors assume that children born in years with higher rainfall had better maternal and infant nutrition. These finding suggest that there is a gender aspect in children's nutritional status since the same results did not appear for the men in the same sample. Furthermore, compared with rainfall in the birth year, rainfall in the years after the birth year has no statistically significant effect on adult outcomes. So it is most plausible that the initial, direct effect of rainfall is on girls' health in the very earliest years after birth. Their results indicate that rainfall affect yield sizes, hence food availability and household income, which lowers the households ability to provide sufficient nutrition to the girl child. It also suggest that weather-induced deprived nutrition as an infant can have lifelong effects.

<sup>&</sup>lt;sup>1</sup> The authors perform an instrumental variable regression analysis. Due to the challenge that rainfall is measured with errors the authors specify an instrumental variable regression where rainfall is instrumented with four analogous rainfall variables measured in the same birth year but in the second- through fifth-closest rainfall stations.

Alderman (2010) reviews studies on the evidence on climate shocks and nutrition and estimate the economic consequences in terms of reduced schooling and lower economic productivity. His review finds that short-term climate shocks do have long-term consequences for children and their future adult lives.

Jensen (2010) states that many low-income countries that depend on rain fed agriculture have limited resources to smooth their consumption over time a mechanism that is very important since agriculture is volatile and sensitive to weather conditions (rainfall) that are out of human's control. One explanation is that low-income countries usually have limited access to credit and insurance markets. Jensen (2010) investigates how the lack of consumption smoothing affects investments in children in the Ivory Coast, or more precisely what the consequences are for children in households with limited ability to transfer resources across time. The paper uses household-level data from 1985-1988 collected by the World Bank and the COte d'Ivoire Ministry of Finance. Rainfall represents both an important input into agriculture and an important source of uncertainty for farmers. The data for rainfall was collected from 41 weather stations and the historical average rainfall for the zones in the sample was calculated for 14 years. If a zone in the sample had more than one standard deviation from the calculated mean it was measured as an adverse weather effects. The regression analysis (OLS fixed effect) confirmed that rainfall was significant in the determination of crop output, farm profits and total household income. Hence, effecting the available income to invest in children. The conclusion states that much needed investments in children suffer dramatically in the presence of adverse weather effects. This results in school-enrolments as well as an increase in overall malnutrition.

My paper is not the first to use the DHS data to investigate child health outcomes, several previous studies use country specific/or merged Demographic Health Survey data for this area of research. For example, by using individual level data from the Demographics Health Survey (DHS) Kadumatsu et al. (2012) investigate the effects of weather fluctuations on infant mortality. The data covers 28 countries in Africa and almost a million births. The weather outcomes are collected from re-analyzing climate models (ERA-40). They investigate the effect of weather on malaria and malnutrition, hence infant mortality. They estimate a panelregression with fixed effect and shows that a simple measure of rainfall during the growing season(s) tied to each child birth is significantly related to infant mortality. Furthermore, rainfall above the site-specific seasonal mean in the relevant growing season diminishes infant mortality but only for babies born in agricultural households in the rainy parts of Africa. It might be reasonable to assume that the vulnerability of the offspring to maternal malnutrition differ with mother or household characteristics, such as occupation, income, or education. They find that drought shocks impose especially hard on babies to parents who work in agriculture, are not well educated, and on babies born around the start of the rains. Kadumatsu et al. (2012) recommend further research in Africa by using a similar approach and statistical methodology. Furthermore, they suggest that DHS data could be useful to look at weather reliance and other outcomes such as child mortality or child health.

With respect to gender-bias Ettyang and Sawe (2016) use data from the 2014 DHS surveys in Kenya and Cambodia to examine stunting levels, and how they are effected by child, maternal and gender inequality. (The paper does not measure any weather related explanatory variable). They discover that children's characteristics were more important in predicting stunting compared to variables related to the mother, household or gender. However, all variables were significantly associated with stunting.

The consequences of weather variables for malnutrition are of interest to non-economists. For example Phalkey et al. (2015) systematically review the current literature on the existing efforts to quantify the impacts of climate change on undernutrition from a public health perspective. In their results they state that they find it difficult to summarize the findings due to the differences in objective and design of the studies in the sample. Therefore, the results are analyzed under the following subsections: climate/weather variables, agriculture variables, household and demographic variables, and individual demographic and health factors on childhood undernutrition. Eight out of the fifteen articles do find a significant impact on rainfall and undernutrition, they also find a significant impact on household socioeconomic and demographic variables. An interesting note is that they find large proportion of the mediating factors are climate sensitive.

In summary the previous literature review is not unambiguous on the effects of drought and child undernutrition. However, several studies do find evidence that there is an impact from drought events on under nutrition in children and that this effects could cause long-term negative consequences for productivity. The gender-bias seems to be in favor of males or females depending on the country/continent, hence the cultural context.

# 3. Zimbabwe country context

Agriculture is the backbone of Zimbabwe's economy. It contributes significantly to both food security and national economic development. The sector accounts for 16 percent of GDP and provides 70 percent of the population with their livelihoods. The main staple food in the country is maize and wheat and the main cash crops are tobacco, cotton, and soybean.

Zimbabwe has one of the most fluctuating rainfall in the world in terms of distribution across time and space. Dry spells and droughts are part of the normal cycle and during an average rainy season it is normal for Zimbabwe to experience four to five dry spells. On average, the higher-altitude areas in the north and east experience lower temperatures than low-lying areas in the west and south. The country is often affected by droughts lasting from one to three years and occurring every five to seven years. Figure 1 shows the average rainfall distribution across the country in an average year as well as the average temperatures collected from the Meteorological Services Department of Zimbabwe (MSD).

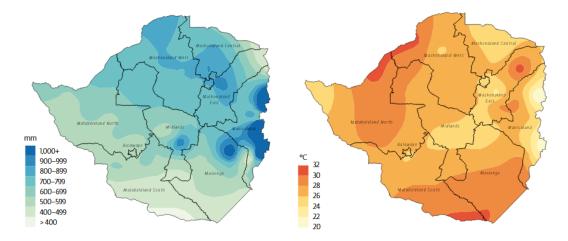


Figure 1 Left: rainfall pattern. Right: average temperature

According to the Human Development Report 2017 drought is one of the most common natural disasters in Zimbabwe, and given that such a large share of the population depends on rain fed agriculture makes the communities' food insecure. Furthermore, over the past century there has been an overall decline in rainfall with approximately 5 percent. The two most recent severe droughts took place 1991/92 and in 2015/16. With a rainfall deficit of around an average of 400 mm. The droughts resulted in 2.8 million people considered food insecure.

In the past, Zimbabwe produced enough food to be self-sufficient and even exported the surplus agricultural products to other countries in the region. Years of economic decline and balance of payment problems reduced the capacity to produce outputs such as food crops and exportable commodities to earn foreign currency. The following political and economic factors (for example hyper-inflation that forced the country to abandon the currency) constrained the government's ability to mitigate the effects of drought after the year 2000. As shown in figure 2, the amount of food aid is much higher from the year 2002, with the exception of the drought crises in 1992/93 known as the worst drought for southern African living memory according to the state of the environment in Southern Africa (1994).

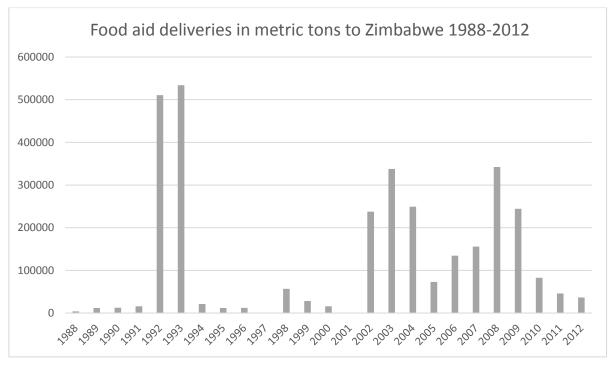


Figure 2 Food aid deliveries in metric tons to Zimbabwe 1988-2012. Source: World food programme, 2018.

Even though the Human Development Index (HDI) has improved by 18 percent during the years 2000-2015, the country still faces many development challenges (UNDP, 2018). In 2015, data from Zimbabwe's Demographic Health Survey (ZDHS) showed that 27 percent of children under age five were stunted, 3 percent are wasted and 8 percent are underweight (See figure 4 below). The numbers also show a noteworthy difference between the different provinces and districts. Since 2005/6 the Zimbabwe DHS has shown a decreasing trend in all the measured variables for children's nutritional status, however the Human Development Report highlights that the effects of climate change could pose a threat to these positive developments in the future. According to the Zimbabwe DHS the prevalence of stunting is the highest among children whose mothers have no education and reside in rural areas.

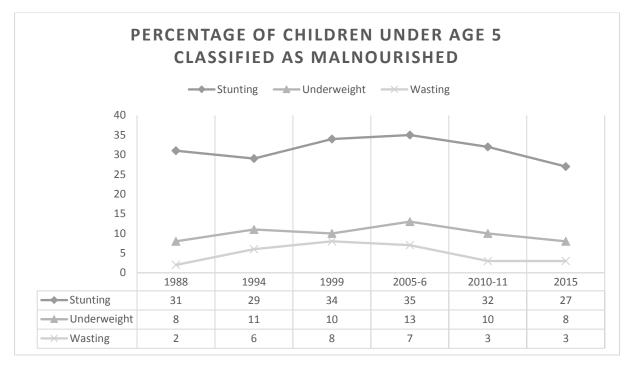


Figure 3 Percentage of children under age 5 classified as malnourished. Source: 2015, ZDHS

An important aspect in Zimbabwe is that there are two common types of agriculture production systems. Large-scale commercial farming and communal areas. Communal areas are most commonly situated in less productive areas of the land and comprise of subsistence farmers. These farmers generally rely on rain-fed agriculture and produce one harvest per year, around April-May. Whereas commercial farming to a larger extent can rely on irrigation should the rain be insufficient. In some areas of the country it is not unlikely that food shortages occur between November-March.

Zimbabwe has four seasons (i) hot season from mid-August to mid-November (ii) main rainy season from mid-November to mid-March, (iii) cool season from mid-May to mid-August, (iiii) post rainy season from mid-March to mid-May. The period before the harvest season presents the time of the highest nutritional stress, between January-March. During this time households rely on staple foods purchased from the market place. This has two major implications on children's nutritional status. First, increased spending's on staple foods leaves less money available to buy high-nutrient goods such as milk, beans, meat, fruits and vegetables. Secondly, the need to work for income increases which leaves less time for child-care. In many communal areas the household head is a women since adult men commonly migrate in search of employment elsewhere. This leaves women in charge of the agriculture work, domestic work and child care.

Another important aspect of the Zimbabwe country context is that he largest share of the population lives in the rural areas, and the rural population is growing more compared to the rural areas, as shown in figure 4 below. 73.5 percent of the children, live in rural areas, compared to urban areas and are directly affected by low food crop production and food insecurity which are exacerbated by more frequent droughts, flooding and unreliable rainfall patterns (FAO, 2017). The major risk facing rural households in Zimbabwe is that of drought (Kinsey et al. 1998), which results in crop failure leading to hunger. This will put additional pressure on the already scarce resources and agriculture production which is the main occupation for people in the rural areas.

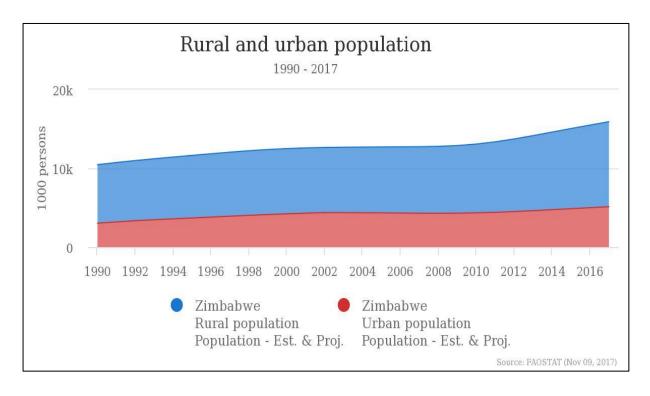


Figure 4 Rural and urban population in Zimbabwe 1990-2016. Source: FAOSTAT Nov 2017

### 4. Data Description

The child health outcome is measured by the variable height-for-age collected from the Zimbabwe Demographic Health Survey (ZDHS). The ZDHS are nationally-representative household surveys that provide data for a wide range of indicators in the areas of population, health, and nutrition. The survey in Zimbabwe is implemented by the Zimbabwe National Statistics agency (ZIMSTAT) and in 2015 the survey covered over 11,000 households. DHS data are cross-sectional in nature and the data on children is collected for children born 5 years previous to the study. The data about children is collected from their mothers. Survey data for Zimbabwe is available from 1998-2015, with the following survey years: 1988, 1994, 1999, 2005, 2010 and 2015. It was not until 1999 that the DHS also started the collection of GPS coordinates for the sample clusters. An important note that will be discussed later on. The extraction of data from the DHS was done using the IPUM website<sup>2</sup>. The IPUM website provides an effective tool to extract the relevant variables from the survey data and services are available free of charge. The relevant variables were extracted into a data-file supported by Stata13.

The height-for-age score is an indicator of chronic malnutrition. According to WHO (2018) a height-for-age score below -200 is considered moderate chronic malnutrition and below -300 severe chronic malnutrition. In other words a height-for-age score below -200 is considered chronic malnutrition and is also referred to as "stunted". The variable reports the difference between the child's height and the median height of a reference population of the same age and sex, expressed in units equal to one standard deviation of the reference population's distribution (this is an important note to keep in mind for the interpretation of the later on results). An anthropometry measure expressed in reference standard deviation units is also known as a Zscore. The data presents the values, reported as units equal to 100 times the Z-score, to preserve two decimal places without requiring the use of a decimal point. The variable height-for-age is measured for surviving children born in the zero to five years before the ZDHS-survey (therefore infant mortality is not reflected in the data). Several other measure for child health outcomes do exist, for example weight-for-age. However, the height-for-age variable is more commonly used to measure current nutritional status<sup>3</sup>, and in this paper the focus is on the longterm child health outcomes. Similar to Ettyang and Sawe (2016) and Hodinott and Kinsey (2001) who also use the height-for-age score as their measure for child health outcomes state that height-for-age is a good indicators of a child's underlying health.

Out of the 20251 observations for the height-for-age variable in my data set there are 3778 values that indicate chronic malnutrition (a height-for-age score below -200), 11678 are not considered stunted and the rest are missing values<sup>4</sup>. In summary that indicates that 24 percent of the children in my sample are classified chronically malnourished. (See the histogram of the dependent variable in annex 1). The average age of the children in the sample is 1.9 years old.

<sup>&</sup>lt;sup>2</sup> available at: https://www.ipums.org/

<sup>&</sup>lt;sup>3</sup> <u>http://121.52.153.178:8080/xmlui/bitstream/handle/123456789/14051/upload-MPhil%20Thesis%202014%20-</u>

<sup>%20</sup>Maha%20Khan.pdf?sequence=1&isAllowed=y page 15.

<sup>&</sup>lt;sup>4</sup> Children may have missing or flagged values for several reasons:

a) The child was not measured as the child refused to be measured, the parent(s) refused to allow the child to be measured, or the child was not present in the household at the time of the interviews,

b) The measurements for the child were outside of the minimum and maximum possible ranges for a child of that age and sex,

c) The combination of height, weight and age are impossible together (for example, the height and weight may be within range individually, the child may be in the 1st percentile for height for age and the 99th percentile of weight for age, or vice versa (these are examples, the exact combinations are given on the WHO web site referenced above, in terms of combinations of Z-scores),

d) The date of birth of the child was not reported to the month. If the age of the child is known in years only, this is not sufficient to calculate the anthropometric Z-scores accurately. Ideally, day, month and year of birth are needed, however DHS imputes the day of birth if it is not given, but the month and year are required to be reported. For the variables in the KR file, children who have died obviously could not be measured and they do not have anthropometric measurements.

To capture weather shocks, I use the Standardized Precipitation-Evapotranspiration Index (SPEI) developed by Vincente-Serrano et al (2010). The SPEI is a multiscalar drought index based on monthly climatic data. An advantage with drought indexes like the SPEI, rather than average rainfall, is that it does not only capture the precipitation, but also considers potential evaporation, information that plays a significant role on local drought conditions. Another advantage of the SPEI is the possibility to use district level data. Potential alternatives to the SPEI do exist. For example the Standardized Precipitation Index (SPI) (see Dinkelman 2017) or the Palmer drought severity index (PDSI). I prefer SPEI due to the already mentioned reasons and because of the inclusion of temperature along with precipitation data allows SPEI to account for the impact of temperature on a drought situation. It also introduces the SPEI measure to the literature on child health outcomes, where as far as I can find it has not been used previously.

The SPEI is a standardized variable with a mean of zero and a variance of one that expresses the water balance in unites of standard deviation from the long-run average. The long-run average is calculated from the period 1901-2012. That means that an index-value of zero corresponds exactly to the long-run water average. For example a value of -1 indicates that the water balance is one standard deviation below the long run average, hence dryer conditions than the long-run average. Since the SPEI measures both positive and negative deviations of the long-term average, I define the drought variable as a dummy variable according to the drought definitions by McKee et al (1993) as shown in the table below. I define moderate drought as SPEI<-1 equal to 1 and 0 otherwise and severe drought as SPEI<-1.5 equal to one and 0 otherwise.

Drought Category	SPEI-value
Moderate drought	-1.00 to -1.49
Severe drought	-1.5 to – 1.99

Table 1 Drought definitions following McKee et al (1993)

Figure 5 below shows the distribution of the moderate droughts on a districts level from the year 1994 to  $2015^5$ . The SPEI-index was collected from the SPEI-website<sup>6</sup>. Each bar represents the fraction of districts each year and month that suffered from moderate drought (SPEI < -1). The figure shows substantial differences between the years. In some years none of the 59 districts suffered from a month of drought whereas some year up to 70 percent of the districts suffered from months with drought.

<sup>&</sup>lt;sup>5</sup> The Republic of Zimbabwe is broken down into 10 administrative provinces, which are divided into 59 districts and 1,200 wards.

<sup>&</sup>lt;sup>6</sup> Available at: http://spei.csic.es/index.html

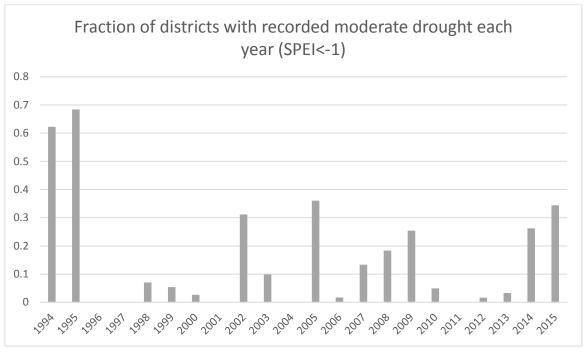


Figure 5 Fraction of districts with recorded moderate drought from 1994-2015

To merge the DHS data with the SPEI index it was necessary to use the GPS locations to match the weather with the location of the survey clusters. Since the DHS only started collecting GPS data in the year 1999 it was not possible to merge the DHS and the SPEI data prior to that year. The merge of the data sets were done in two main steps. First, the DHS data was merged with the DHS geographic data<sup>7</sup> (that contains the GPS coordinates) using the DHS-ID<sup>8</sup>. Secondly, the DHS (including the GPS coordinates) was merged with the SPEI data that also continued the GPS coordinates. This way, the individuals in the DHS data all had a corresponding measure for drought exposure in their district, year and month of birth.

Besides the main treatment variables for moderate and severe drought, and if gender and rural/urban status has an effect on the outcome. I include control variables for child, maternal and household characteristics. These are included to control for confounders in the model.

The child variables include the child's year of birth and month of birth as well as the birth order of the child<sup>9</sup>. The information of birth year and birth month is used to identify the child's exposure to drought in the month of birth. The variable birth order of the child was included since previous studies have shown that the birth order has a significant effect on a child's nutritional status, and a majority of those studies suggest a negative impact of a child's nutritional status (Hortson 1988; Alderman et al 2006).

The household and maternal variables include a household wealth index, rural or urban living conditions, the mother's occupation, and the mother's total years of education. The household's wealth refers to the relative wealth of the household where the mother and the child lives. According to Kadumatsu et al. (2012) children that are born in poor households are more sensitive to drought shocks. The variable is divided into quintiles from the poorest (code 1) to

<sup>&</sup>lt;sup>7</sup> This variable was downloaded from DHS-webpage and converted from shape-files into Stata-files.

<sup>8</sup> The DHSID is a 14-character DHS identification code for DHS clusters, it uniquely identifies clusters across samples. Secondly, the SPEI was merges with the DHS data using the GPS coordinates for the clusters and the year and month of the individual. <sup>9</sup> The variable month of birth was selected since Wright et al. (2001) do find a small but significant increase in levels of underweight takes

place during January-March.

the richest (code 5). The wealth index is a composite measure of a household's cumulative living standard. It's calculated by using common data on a household's ownership of selected material assets, such as TVs and bikes; materials used for housing construction; and types of water access and sanitation facilities. The variable household wealth was selected, over the mother's income variable due to the country context of Zimbabwe. An alternative variable would have been "women's earnings". However, the variable is measured in Zimbabwean dollars, which were circulated from 1980 and abandoned during the economic crises in April 2009. Therefore, the variable is not consistent over the time period for this data set.

Furthermore, research has found that the vulnerability to drought shocks also applies to children that are born to parents that work in agriculture. Therefore, I include the variable on mother's occupation. The data on mother's current occupation is divided into several categories of jobs. The variables is transformed into a dummy variable for occupation within agriculture (self-employed or employed in agriculture), and 0 otherwise (0 also includes "not currently working" which is almost 50 percent of the survey answers).

The compilation of the dataset creates a repeated cross-sectional data set. Note that a repeated cross-section data is created where a survey is administered to a new sample of individuals at successive time points. This makes repeated cross-section data different from a true panel data set since it is not the same individual that has been followed at the different points in time. The major limitation of repeated cross-sectional data is that the same individuals are not followed over time, so that individual histories are not available for inclusion in a model. On the other hand, repeated cross-sections suffer much less from typical panel data problems such as nonresponses, and are very often substantially larger, both in number of individuals or households and in the time period that they span (Verbeek, 2018).

In summary, the merged variables from the DHS and the SPEI create a repeated cross section data set, with N=15507 number of observations for the years 1999-2015 in Zimbabwe. This is the longest timeframe where all selected variables are measured and available.

In table 2 below, all the above mentioned variables are summarized. Note that the total number of observations are not the same for each variable. This is due to missing or flagged values in the survey data. The height-for-age score has the largest number of missing values (explanation in footnote five).

#### **Table 2 Summary Statistics**

Variable	Ν	Mean	Std. Dev	Min	Max
Height-for-age,	15507	-112.785	138.9695	-600	598
Moderate drought (SPEI<-1)	20251	0.14661	0.3537255	0	1
Severe drought (SPEI<-1.5)	20251	0.0471582	0.2119823	0	1
Rural	20584	0.702632	0.4571111	0	1
Household Wealth index	20584	2.869439	1.421785	1	5
Mother years of education	20580	8.360794	3.019246	0	21
Mother work in agriculture	20478	0.1492766	.3563697	0	1
Kids birth order	20584	2.767715	1.880916	1	16
Female	20584	0.498445	0.5000099	0	1

Notes. Individual level data from the ZDHS for children under 5 years of age born between the years 1994-2015. \*In my statistical analysis SPEI index will be defined as moderate drought and severe drought, in line with the definitions by McKee et al (1993).

### 5. Econometric analysis

To find the main effect of exposure to drought during the time of birth on the health status of the child, I estimate equation (1) below using a repeated cross section data set from Zimbabwe. In this study the key measure of health outcome is the height-for-age score, which measures the difference between the individual child's heights compared to the median height of the reference population. Any height-for-age score below -200 is regarded as stunted according to WHO, and stunting is an indicator of chronic malnutrition.

Equation 1 presents the baseline regression equation

#### Equation 1

$$\begin{split} Z_{ihcdt} &= \beta_0 + \beta_1 Drought_{dym} + \beta_2 Rural_{ihcdt} + \beta_3 HouseholdWealth_{ihcdt} + \beta_4 MotherEducation_{ihcdt} + \\ & \beta_5 BirthOrder_{ihcdt} + \beta_6 MotherWork_{ihcdt} + \beta_7 Female_{ihcdt} + \mu_d + \delta_y + \omega_t + \epsilon_{ihcdymt} \end{split}$$

where; Z is the vector of the child health outcomes, measured as height-for-age expressed in units equal to one standard deviation of the reference population's distribution for child i living in household h, in community c, in district d, and surveyed in year t. Drought<sub>dym</sub> is the main treatment variable in this equation and is measured by the SPEI index, the indices y an m stand for year and month of the child's birth. I estimate two variants of the equation to examine the effect of moderate and severe drought respectively. First, by using the SPEI dummy variable defined as moderate drought, SPEI<-1 (i.e., if the district's SPEI is at least one standard deviation below the long run mean), and secondly for severe drought, SPEI<-1.5 (i.e., if the district's SPEI is at least 1.5 standard deviations below the long run mean) (McKee, et al 1993). The drought variable is measured for district d, birth year y, and month of birth m. For all drought variable, the main effect is captured by  $\beta_1$ . A negative estimate of  $\beta_1$ , would suggest that exposure to drought (severe/moderate) lowers the height-for-age score of the child. Intuitively, this implies that exposure to drought at the time of birth increases the likelihood of a lower HAZ-score with all values below -200 being considered stunted.

Survey year fixed effects are included to control for time varying factors across the survey years. The model also controls for the district fixed effect  $\mu_d$ , as well as the year of birth fixed effect  $\delta_t$ . Birth year fixed effect is included to absorb temporal shocks across the years in which the children were born and district fixed effect other local variations that may affect the health outcome.  $\epsilon_{ihcdymt}$  is the error term. Given the structure and size of the data-set the equations are estimated by using pooled-OLS with fixed effects. I present robust standard errors clustered at the primary sampling unit

I have a large sample size (N=15505). I use robust standard errors accounting for potential heteroscedasticity in all my estimates. Even if there is no heteroscedasticity, the robust standard errors will become just conventional OLS standard errors. Thus, the robust standard errors are appropriate even under homoscedasticity (Cameron and Trivedi 2010). Moreover, due to potential risk of multicollinearity in my model I checked the correlation matrix for the coefficients in my model. The model does not have any correlations <0.5 therefore there is little risk of multicollinearity in the data. See appendix 2 for correlation matrix of the coefficients in the model<sup>10</sup>.

<sup>&</sup>lt;sup>10</sup> Allison (1999). Suggests correlations above 0.6 as a "let's start-worrying-about-multicollinearity-threshold".

An essential part of my research strategy is that, local droughts should be as good as random. Hence, local droughts are unlikely to be correlated with for example with every local political change or other local change that could affect the child health outcome.

I estimate<sup>11</sup> equation (1) for the full sample separately for each definition of drought. This is followed by separate estimates for the female and male subsamples based on results by Dinkelmans (2017). Her conclusion is that males are more sensitive to early life exposure to drought. However, Maccini and Yang (2009), and Ettyang and Sawe (2016) find that the girl child health outcomes are more effected by insufficient rainfall or drought compared to the boys.

Another way of investigating the gender effects on child health outcomes is to create an interaction term between Drought and Female dummy variables which captures the effect in the same estimate rather than repeating the estimates on the subsamples for male and females. This makes it possible to compare the effects within the same model, see equation 2.

#### **Equation 2**

$$\begin{split} Z_{ihcdt} &= \beta_0 + \beta_1 Drought_{dym} + \beta_2 Rural_{ihcdt} + \beta_3 HouseholdWealth_{ihcdt} + \beta_4 MotherEducation_{ihcdt} + \\ \beta_5 BirthOrder_{ihcdt} + \beta_6 MotherWork_{ihcdt} + \beta_7 Female_{ihcdt} + \beta_8 Drought_{dym} * Female_{ihcdt} + \mu_d + \delta_y + \omega_t + \\ \epsilon_{ihcdymt} \end{split}$$

Where  $\text{Female}_{ihcdt}$  \*Drought<sub>dym</sub> is the interaction term that measure the impact of drought times the dummy variable for gender where 1 equals female and 0 equals male.

The ZDHS states that children born in the rural areas are more prone to stunting. Therefore, in equation 3, I include an interaction between drought and rural status to investigate this statement in this sample. I estimate equation (2) and (3) for both definitions of drought.

#### **Equation 3**

$$\begin{split} Z_{ihcdt} &= \beta_0 + \beta_1 Drought_{dym} + \beta_2 Rural_{ihcdt} + \beta_3 HouseholdWealth_{ihcdt} + \beta_4 MotherEducation_{ihcdt} \\ &+ \beta_5 BirthOrder_{ihcdt} + \beta_6 MotherWork_{ihcdt} + \beta_7 Female_{ihcdt} + \beta_8 Drought_{dym} * Rural_{ihcdt} \\ &+ \mu_d + \delta_y + \omega_t + \epsilon_{ihcdymt} \end{split}$$

Where  $Drought_{dym}$  \*Rural<sub>ihedt</sub> is the interaction term between drought and the individuals living in rural areas. One could expect drought to have a larger impact people in the rural areas since they are more dependent on agriculture and agricultural yields are dependent on rain-fed water resources rather than irrigation.

<sup>&</sup>lt;sup>11</sup> I use the reghtfe command in Stata. The regdfe is a Stata package that runs linear and instrumental-variable regressions with many levels of fixed effects, by implementing the estimator of Correia (2015).

# 6. Results and Discussion

Table 3 presents the results from estimating equation (1) in the previous chapter, were the first estimate is for moderate drought and the second one for severe drought. For each outcome I present my estimates on the full sample (column 1) as well as the results from the male (column 2) and female (column 3) subsamples. Column 4-6 show the same results but for the estimates with severe drought. Under each coefficient I show robust standard errors.

The results indicate that exposure to moderate drought increases the likelihood of a child being stunted. Specifically, exposure to at least a one standard deviation below the long run SPEI average in a given district is associated with 8.47 negative standard deviations in height-forage below the mean reference population. The effect is significant at 5 percent. The effects of moderate drought has the same sign for the separate estimates on the male and female subsamples, however the drought coefficient is not significant.

The variables household wealth is significant on the 0.1 level, in all sample estimates. This means that moving up one quintile in the household wealth distribution is associated with an increase of 7.391 standard deviations of the height-for-age. The estimates are also significant, with positive signs for the male (5.775) and female (9.387) subsamples, the effect is even larger on the female subsample. Previous articles have concluded that household wealth is an important determinant of the child's nutritional status. For example Jensen (2000) finds that insufficient rainfall effects household income negative, hence lowering investments in the household's children which increases the risk of malnutrition. Household wealth has a significant impact on children's nutritional status in my model.

The mother's level of education (one more year of education) is associated with an increase of 3.470 standard deviations of the height-for-age. The effect is also positive and significant for the male (3.799) and female subsample (2.966). This results supports the conclusion from Phalkey et al (2015) who find that a significant association between malnutrition and the mother's level of education (they find this result in four out of nine reviewed articles). Similarly, Kadumatsu et al. (2012) conclude that drought shocks impose especially hard on babies to parents that are not well educated.

When the regression is repeated with the measure for severe drought (-1.5 standard deviation from the long-run SPEI average) the variable becomes insignificant for the full and male subsample. However, for the female subsample the drought coefficient is associated with a negative 20.51 standard deviation from the reference population's distribution of height-for-age value. The coefficient is significant on 1 percent level. With caution, this result can be interpreted as supporting the hypothesis that there is gender bias in how households divide their resources among the children.

Again, the variables household wealth and total years of mother's education are significant on the 0.1 percent level, in all sample estimates. This means that moving up one quintile in the household wealth distribution is associated with an increase of 7.310 standard deviations of the height-for-age. The impact is for the male subsample is (5.730) compared to the female (9.320). The mother's level of education (one more year of education) is associated with an increase of 3.477 standard deviations of the height-for-age. The effect is larger on the male subsample (3.800) compared to the female subsample (2.968).

The variable rural, kid birth order, mothers work and female are insignificant in all estimates, regardless of the definition of drought. Kadmatsu et al. (2012) do find that children in

households where the mother occupation is in agriculture are more vulnerable to drought. In my analysis the mother occupation does not have a significant effect on the child's nutritional status. One explanation to this could be that in the survey data almost 50 percent of the women answered that they were currently not working. Since other data indicate that 70-80 percent of the population in Zimbabwe relies on agriculture for food and income it could be that they have crop or animal production solely for household needs and therefore do not report it as working in agriculture. The R-sq values is between 10.3 - 10.9 for all estimates.

	Full sample	Male	Female	Full sample	Male	Female
	1	2	3	4	5	6
Moderate Drought (SPEI<-1)	-8.472*	-8.484	-8.313			
	(3.657)	(5.132)	(4.845)			
Severe Drought (SPEI<-1.5)				-10.35	-0.818	-20.51**
				(5.905)	(8.824)	(7.656)
Rural	-4.85	-2.173	-7.418	-4.989	-2.335	-7.451
	(4.416)	(5.875)	(5.779)	(4.414)	(5.875)	(5.78)
Household wealth	7.391***	5.775**	9.387***	7.310***	5.730**	9.320***
	(1.321)	(1.817)	(1.691)	(1.321)	(1.818)	(1.69)
Mother years of education	3.470***	3.799***	2.966***	3.477***	3.800***	2.968***
	(0.508)	(0.674)	(0.696)	(0.507)	(0.674)	(0.696)
Kids birth order	0.912	1.223	0.431	0.917	1.227	0.428
	(0.686)	(0.894)	(0.969)	(0.686)	(0.894)	(0.968)
Mother work	2.631	1.551	2.638	2.633	1.519	2.733
	(3.536)	(4.799)	(4.881)	(3.541)	(4.794)	(4.879)
Kid sex	1.003			0.969		
	(1.998)			(1.998)		
Ν	15505	7739	7766	15505	7739	7766
R-sq	0.103	0.109	0.107	0.103	0.108	0.107
Birth year, survey, district FE	Y	Y	Y	Y	Y	Y

#### Table 3 Estimation results for the baseline equation.

Notes. Level of significance: \* p < 0.05, \*\* p < 0.01, \*\*\* p < 0.001. Robust standard errors clustered by DHS-ID are shown in the parenthesis under each coefficient. All regressions have a full set of birth year, year of survey and district fixed effects.

In table 4, the results from estimating equation 2 and 3 from the previous chapter are presented. The interaction term is created by multiplying severe/moderate drought and the sex of the child as well as severe/moderate drought and rural/urban status. The only interaction variable that shows significant results is the Severe drought \* Kid sex (-22.98\*), which indicates that gender

could potentially matter for the outcome of malnutrition. The signs for all variables are consistent with the signs from the previous estimates for the full, female and male samples. Except for the interaction variable for severe drought \* rural status that shows a positive sign. The R-sq is 10.3 percent.

	Interaction: Moderate drought * Female	Interaction: Moderate drought * Rural	Interaction: Severe drought*Female	Interaction: Severe drought ' Rural
	1	2	3	4
Moderate drought * Female	-5.139			
	(5.96)			
Moderate drought * Rural		-5.484		
		(7.045)		
Severe drought * Female			-22.98*	
			(10.31)	
Severe drought * Rural				13.67
				(11.82)
Moderate drought (SPEI<-1)	-5.87	-12.40		
	(4.928)	(6.302)		
			1.11	-20.16
Severe drought (SPEI<-1.5)			(8.365)	(10.528)
Female	1.759	1.001	2.069	0.991
	(2.143)	(1.998)	(2.031)	(1.997)
Rural	-4.839	-5.692	-4.913	-5.696
	(4.413)	(4.535)	(4.41)	(4.454)
Household wealth	7.406***	7.373***	7.353***	7.303***
	(1.321)	(1.321)	(1.321)	(1.321)
Mother years education	3.465***	3.471***	3.468***	3.482***
	(0.507)	(0.508)	(0.507)	(0.507)
Kids birth order	0.908	0.916	0.902	0.926
	(0.686)	(0.686)	(0.686)	(0.686)
Mother work	2.636	2.595	2.619	2.593
	(3.534)	(3.535)	(3.533)	(3.541)
N	15505	15505	15505	15505
R-sq	0.103	0.103	0.103	0.103

#### Table 4 Estimation results for the interaction coefficients

Notes. Level of significance: \* p < 0.05, \*\* p < 0.01, \*\*\* p < 0.001. Robust standard errors clustered by DHS-ID are shown in the parenthesis under each coefficient. All regressions have a full set of birth year, year of survey and district fixed effects.

If a child lives in the rural or urban areas does not have a significant impact in the model. This is unexpected since the DHS points out that children are more likely to be stunted in the rural areas. Furthermore, Wright et al. (2001) find that rural areas are more sensitive to seasonal aspects of malnutrition, however he uses the weight-for-age as a measure of the child health outcome and that measure is more associated with short-term nutritional deficit whereas my variable measure long-run effects hence chronic malnutrition.

Table 7 in appendix 3 reports on the outcome of an alternative model. There is a possibility that the child health outcome is more effected by the cumulative exposure to drought in the year of birth rather than the exposure around the time of birth (month and year of birth). Therefore, I repeat the estimates 1 and 4 from table 3 with a different specification for drought. The new definition of drought account for the total months with exposure to drought in the year of birth (average months with moderate drought SPEI<-1 and severe drought SPEI<1.5)

Comparing these results to the reported outcomes in table 3, we see that the main treatment variable continues to have a negative sign. However, none of the drought variables are significant. This indicates that my results are not robust for an alternative measure of drought exposure.

### 7. Conclusions

This paper investigates how child health outcomes are effected by exposure to drought at the time of birth in Zimbabwe from the year 1999-2015. The height-for-age score measures the child's health outcome, also known as the measure for chronic malnutrition. As stated in the first chapter, this paper aims to answer the following research questions (i) how does exposure to drought, at the time of birth, affect child health outcomes in Zimbabwe? (ii) How does the impact vary across gender? (iii) Are children in the rural areas more sensitive to early-life exposure to drought?

By using data on drought defined as moderate and severe drought using the SPEI and data from the ZDHS, I obtain a few significant results from my econometric analysis. The results suggest that exposure to moderate drought at time of birth could be associated with child malnutrition where a drought (a -1 standard deviation from the long-run SPEI average) is associated with - 8.472 deviations from the mean reference population's height-for-age measure. Severe drought had a significant effect on the female subsample with a -20.51 deviations from the reference population. However, the results were not significant for the full- or male sample. Neither were the estimates from my alternative model that defined cumulative drought exposure in the year of birth. However, the signs of the variables remained the same.

My results do not support a clear gender bias. For severe drought the variable is significant for the female sample, which would indicate that female children in Zimbabwe are more vulnerable to drought compared to male children. This could possibly indicate gender-bias in the household's resource distribution, where boys are favored over girls in the household when resources become scarce. However, this hypotheses requires more research before it could be accurately established. Similarly, urban versus rural status does not show significant results in my estimates for any definition of drought or when they are interacted in the model. In line with previous research I do find that household wealth and the mother's educations has a positive association with a child's nutritional status.

Food aid and other feeding programmes could mitigate the effects of drought on children's health outcomes, and possibly explain some of the insignificant results in this analysis. For example the World Food Progarmme (WFP) has been active in Zimbabwe since 2002 with, among others, distributing food and implementing child feeding programs. Furthermore, neither of my models include the effects of migration due to drought as well as remittances from relatives working abroad, this could also mitigate the effects of drought on the child health outcome. A future research area could therefore be to investigate to what extent food aid improves the child health outcomes when exposed to income chocks such as drought, and how it affects the migration patterns for the children.

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# 9. Appendix



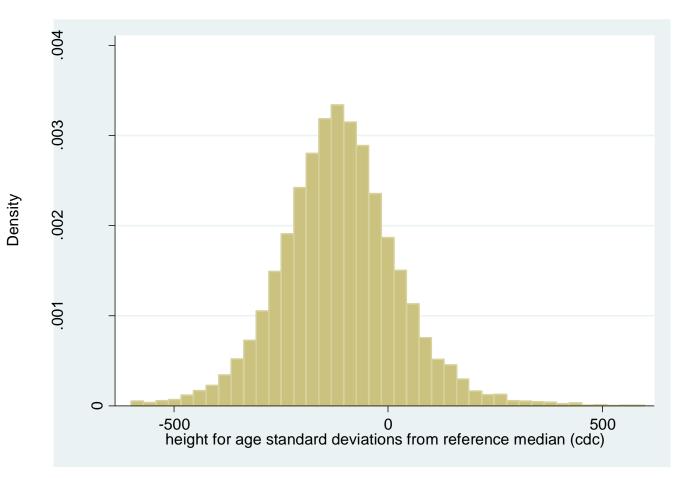


Figure 6 Height-for-age standard deviations from reference median

### Appendix 2

#### Table 5 Correlation matrix (moderate drought)

Correlation matrix of coefficients (Moderate Drought)							
e(V)	Severe Drought	Rural	HouseholdWealth	Mother education	BirthOrder	Motherwork	Female
Severe Drought	1						
Urban/Rural	-0.0219	1					
HouseholdWealth	0.0297	0.5045	1				
Mother education	0.0316	0.0709	-0.2411	1			
BirthOrder	-0.0139	-0.0687	-0.0188	0.2779	1		
MotherWork	-0.029	-0.0817	-0.0502	0.083	-0.0358	1	
Female	-0.0825	0.0033	0.033	-0.0021	0.026	-0.0548	1

#### Table 6 Correlation matrix (severe drought)

Correlation matrix	of coefficier	nts (Severe Drou	ıght)				
e(V)	Severe Drought	Rural	HouseholdWealth	Mother education	BirthOrder	Motherwork	Female
Severe Drought	1						
Rural	-0.0655	1					
HouseholdWealth	0.0045	0.5045	1				
Mother education	-0.032	0.0734	-0.2403	1			
BirthOrder	-0.0351	-0.0672	-0.0182	0.2788	1		
Motherwork	0.0075	-0.0827	-0.0506	0.0822	-0.0361	1	
Female	-0.0508	0.0029	0.0324	-0.001	0.0262	-0.0553	1

### Appendix 3

#### Table 7 Alternative drought measure model<sup>12</sup>

	Full sample	Full Sample
	1	2
Madarata Draught (avarage months with		
Moderate Drought (average months with SPEI<-1 in the year of birth)	-5.266	
<b>,</b> ,	(4.774)	
Severe Drought (average months with		
SPEI<-1.5 in the year of birth)		-7.542
		(8.298)
Rural	7.343***	7.318***
	(1.321)	(1.321)
Household wealth	3.476***	3.476***
	(0.508)	(0.507)
Mother years of education	2.573	2.572
	(3.536)	(3.539)
Kids birth order	0.98	0.981
	(1.998)	(1.999)
Mother work	-4.959	-4.989
	(4.423)	(4.424)
Female	0.924	0.924
	(0.686)	(0.686)
N	15505	15505
R-sq	0.0961	0.0961
Birth year, survey, district FE	Y	Y

Notes. Level of significance: \*p<0.05, \*\*p<0.01, \*\*\*p<0.001. Robust standard errors clustered by DHS-ID are shown in the parenthesis under each coefficient. All regressions have a full set of birth year, year of survey and district fixed effects.

<sup>&</sup>lt;sup>12</sup> New definition of drought account for the total months with exposure to drought in the year of birth (average months with moderate drought SPEI<-1 and severe drought SPEI<1.5)