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The Effects of Natural Disasters on Health:

The example of Zambia

Bachelor Thesis

Submitted by:
Julius M.M. Siebenaller
14-619-076

Supervisor:
Prof. Anthony Strittmatter, Ph.D.

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Abstract

Developing countries face a high burden of disease and are limited on their growth path. Shocks, including natural disasters, have further adverse effects of growth in the short- and the long-run. This thesis analyzes effects that natural disasters have on child health. The setting is provided by a drought that affected about 1.2 million people in two regions in Zambia during the year 2005. A demographic and health survey is employed and the indicators of interest are the WHO height for age and weight for age Z-scores (HAZ, WAZ), which are measured two years after the shock took place. The estimation strategy combines a DID approach with additional specifications to account for the age-specific growth path of children. The findings indicate a significant impairment in the long-term growth of exposed children, although the results for fixed effects and the estimations for the WAZ are insignificant.

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1 Introduction

Health status is a remarkable indicator for the well-being of a country and the effects of health are significant contributors to growth (Barro, 2013). But health, as a form of human capital, is also vulnerable to shocks, which alter the growth path (Folland et al., 2016, p.141-148). Dupas (2011), for example, finds that developing countries face a high disease-burden and thus, they are particularly vulnerable to health shocks and the respective interference with growth (Hoddinott and Quisumbing, 2010). According to the fetal origins hypothesis, especially unborn, newborn and young children are affected by health shocks and might sustain life-long consequences (Almond and Currie, 2011; Baird et al., 2012; Lumey et al., 2007).

The purpose of this thesis is to analyze the effects of natural disasters on children's health in developing countries. A demographic and health survey (DHS) for Zambia is employed and matched with data on a drought that occurred during the year 2005, as indicated by EM-DAT. To refine the estimation of shock exposure, the estimation strategy combines the approaches of Fuentes-Nieva and Seck (2010) and Rieger and Trommlerová (2016), by accounting for the age-specific path of child growth. The empirical model assesses the effect of the drought on relevant health indicators by employing a DID estimation for the birth-date and birth-region, which is further specified to control for child growth.

This study finds that shock exposure significantly lowers a child's age-specific height below the age-specific mean, indicating a severe interference in their growth path. Fixed-effects estimation at the mother and household level result in insignificant impairments. The children are also indicated to have a weight below the age-specific mean, but these results are insignificant in either setting. The same accounts for applying a logarithmic function of age for the weight profile, but an implausible, though likewise small and insignificant, increase in weight for mother fixed effects.

The thesis is structured as follows: Section 2 reviews the relevant literature on models of health development, on the underlying biocultural mechanisms and on catastrophe analysis and famine studies. Section 3 describes the data, including the country and variables selection. The estimation strategy is presented in Section 4. Section 5 describes the results with a discussion of the findings. Section 6 concludes.

2 Literature Review

2.1 Health Development

Grossman (1972) is one of the first to model the demand and the production of health. Health - in Grossman's notion "healthy days" (1972, p.227) and defined as a stock variable - yields direct utility and also contributes to one's ability to be more productive and to loose less time due to sickness. Grossman states the efficiency enhancing effect of education on health capital.[1] Furthermore, Bolin (2011) explains the underlying mechanisms of age, income and education which influence the health of the individual. Also, the influence of family-decisions in households and uncertainty are analyzed and the models are confirmed from an empirical point of view.

Heckman (2007) shifts the focus towards underlying mechanisms in health formation and relevant periods of development. Capabilities - cognitive, non-cognitive, and health capabilities - are formed in an intergenerational setting as a result of the initial capability endowment which is influenced by both parental investment and parental capabilities.

Baker and Stabile (2011) refer to Heckman (2007) in explaining childhood health, but extend the view to include insults - injuries, diseases or chronic conditions - to health. They further explain influences concerning in utero and infancy health, as well as the role of parental characteristics and behavior.

A life-time approach in health production is introduced by Strauss and Thomas (2008). The authors focus explicitly on health inputs, the respective environment, constant and time-varying demographic characteristics, as well as the individual's health endowment, which all influence the health stock and the respective growth path.

Dupas (2011) provides more context specific modifications by separating health investment in preventive and remedial care. These influence the occurrence and the impact of health shocks. Hence, health is based on the health level in previous periods and develops according to the outcome of these shocks, which results from prevention and coping mechanisms.

[1] Grossman (1972) rules out possible effects of education on the depreciation rate of health capital which are of specific interest in Barro (2013). Shifting the focus towards the influence of health on economic growth, Barro (2013) explains that health capital - next to physical capital and schooling - directly influences output, but moreover it reduces the depreciation of both forms of human capital.

2.2 Biocultural Mechanisms

The "fetal origins hypothesis," also known as "Barker hypothesis," presents a fundamental understanding of the development of health over time, laying out the foundation for the so called "Developmental Origins of Health and Disease (DOHaD)" (Barker, 1997; Gluckman et al., 2010, p.6-14).

Focusing on interactions between a fetus' nutritional status and diseases later in adulthood, Barker and Osmond (1986) and Barker (1997) explain that adverse environment in early life, particularly undernutrition, require adaptations of the fetus to ensure survival in the short-run, but often go ahead with trade-offs in the long-run.[2]

The explanations of Godfrey and Barker (2000) reveal that newborns with low height and weight are at risk of several long-term diseases, which increase the likelihood of morbidity and mortality.[3] They also evaluate that intergenerational effects influence health outcomes of children. Specifically maternal low birth weight is transmitted across generations, which is also confirmed in Victoria et al. (2008, p.346-347), though the extent of these effects decreases over time. Victoria et al. (2008) further specify that undernutrition until year two is most severe and limits growth and lowers educational level and economic status in adulthood. Martorell and Zongrone (2012) capture the findings on intergenerational effects and describe that the process of "wash[ing] out" (p.308-310) requires a timespan over several generations. They expand on Victoria et al. (2008) and emphasize the relevance of "the first 1000 days" (p.304-311) from conception onwards.

Rieger and Trommlerová (2016) provide a thorough analysis of factors that influence child growth by investigating Demographic and Health Surveys for over 50 countries. They explain that child growth, respectively growth faltering, follows an age-specific growth path. Especially, a wide range of characteristics by the side of the child, the mother and household, as well as by the side of the country, have a significant influence on child growth. Parts of the estimation strategy and particularly the control variables are derived from their analysis.

[2]Especially ischaemic and coronary heart disease, strokes, diabetes and hypertension in adulthood (Barker and Osmond, 1986, Barker, 1997).

[3]Including - besides coronary heart disease and hypertension - increased blood pressure from the prepubertal period onwards, insulin resistance at adult age, low glycolisis rates or reduced postprandial glucose oxidation (Godfrey and Barker, 2000).

2.3 Catastrophe Analysis and Famine Studies

The Dutch Hunger Winter, during 1944 to 1945, is one of the most extensively studied events to assess the effect of health shocks on health formation and development. In this setting, Yarde et al. (2013) analyze birthweight outcomes and menopause age by comparing adults born between 1943 and 1947 whose mothers were exposed to food rationing and famine during pregnancy. The group finds that exposure increased women's hazard of natural menopause, whereas birthweight was negatively associated with the hazard. Scholte et al. (2015) utilize the cross-country variations in famine exposure for men and analyze economic and health outcomes some fifty to sixty years after the famine. The employment rates are significantly lower for those exposed during the first or second trimester of gestation and labor income is reduced for all exposed trimesters on an insignificant level. Rates of hospitalization are increased, which is highly significant for all gestational exposed groups.[4]

The China Great Leap Forward Famine from 1959 to 1961 is another extensively studied event in the analysis of mal-, respectively undernutrition, and health shocks. Kim et al. (2016) examine the China Health and Retirement Longitudinal Study (CHARLS) from 2011 and compare outcomes in adulthood for those who were rural-born between 1954 to 1966, thus adding five year pre- and post-famine comparison groups. For those exposed in utero, increases in famine intensity, as measured by province- and year-specific average, respectively weighted death rate, adversely effect the formation of human capital in terms of cognitive skills and physical health.[5]

Fung and Ha (2010) utilize the time and regional variations of the famine's impacts and apply an intergenerational perspective for the following two generations. Individuals born during the famine are more likely to be disadvantaged in both physical conditions and cognitive skills formation and these impairments are transmitted across generations.[6] Almond et al. (2007)

[4]The rise in hospitalization rates came along with significant increases in cardiovascular-disease related referrals, but not with cancer-related ones, hence their analysis supports the fetal origins hypothesis (Scholte et al., 2015).

[5]Particularly by causing and aggravating walking difficulties, vision disabilities, speech impediment, recall error or by increasing the probability to suffer from stroke (Kim et al., 2016).

[6]The famine increases the risk of stunting and those affected are found to have a lower BMI and less years of schooling, which is also found to be significant in following generations, thus exacerbating the initial effect (Fung and Ha, 2010).

focus on socioeconomic implications of famine exposure by examining the 2000 Population Census of China and the natality micro data for Hong Kong. The famine poses significant disadvantages on those exposed, which results in different outcomes for men and women.[7] A further noticeable finding is that famine exposure induces shifts in the male-female ratio in the population by relatively increasing mortality rates of men and as a result of women being more likely to give birth to girls. Hence, the famine's impacts are carried across generations.[8]

Turning to natural disasters, similar outcomes are found to result from such adverse conditions. De la Fuente and Fuentes-Nieva (2010) show that climate shocks - droughts, floods, frosts, earthquakes and hurricanes - significantly increase morbidity of children. They examine stated sickness and suffering from a shock one, respectively six months prior to the surveys for seven states in Mexico during the period from November 1998 to November 2000.[9]

The work of Fuentes-Nieva and Seck (2010) motivates the approach that is employed in this thesis. In the targeted group of children younger than five years, Fuentes-Nieva and Seck (2010) analyze stunting, wasting and malnourishment as outcomes of being exposed to weather-related shocks before or after birth.[10] Relying on Demographic and Health Surveys (DHS) for Ethiopia, Kenya and Niger, they match shocks that affect at least one million people. Variations in birthplace and -date, with respect to shock occurrence and duration, provide the setting to employ a DID estimation. Whereas their results are mixed for Kenya and Niger in general and for wasting in Ethiopia, Fuentes-Nieva and Seck find significant increases in stunting

[7] Men were found to have significantly increased likelihoods of being illiterate, not being in the workforce or depending on financial support from household members. They were also less likely to be married or if married, then later in life. On the other hand, women were found to be married to men with lower educational status. (Almond et al., 2007)

[8] Almond et al. (2007) explain that a potential explanation can be found in the Trivers-Willard hypothesis, which states that "natural selection should favour parental ability to adjust the sex ratio of offspring produced according to parental ability to invest," (Trivers and Willard, 1973, p.90). Unfortunately, an in-depth analysis of this hypothesis would go beyond the scope of this thesis.

[9] On the other hand, a highly implausible finding in their sample is that households with a better socioeconomic status are more likely to incur children morbidity, which is explained as resulting from a biased illness-perception, common in households with a lower socioeconomic status (De la Fuente and Fuentes-Nieva, 2010, p.115-122).

[10] A more detailed explanation of stunting, wasting and malnourishment is provided in Section 3.

and malnourishment for those affected in Ethiopia. Thus, they confirm that the adverse effects of shock exposure are, at least partially, revealed in the short run. Hence, this indicates a risk in the path of health formation.

3 Data and Variables Selection

3.1 Country and Shock Selection

As there are only a few suitable panel datasets available, this thesis relies on a cross-sectional dataset and employs a synthetic difference-in-difference estimation strategy, similar to Fuentes-Nieva and Seck (2010). The data are obtained from a Demographic and Health Survey (DHS) (Central Statistical Office (CSO), 2009*b*). Data on the shock is provided by EM-DAT, the International Disaster Database (Guha-Saphir, 2018).[11]

The restrictions for choosing a dataset were as follows: (1) In the five years prior to the interview period, one significant shock had to take place in the specific country and (2) the shock must not be surrounded by other incidents that occurred in the preceding interval. (3) In line with Fuentes-Nieva and Seck (2010), the shock was considered significant if it affected more than 1,000,000 people in the country, which was indicated by EM-DAT (Guha-Saphir, 2018).

Freire-González et al. (2017, p.197-202) explain that droughts generally leave a country's physical capital unaffected, although they might affect human capital in the short- and long-term. Therefore, droughts provide the, at least from an analytical point of view, most appropriate setting to clearly separate the direct shock effects from indirect and long-term effects that would further interfere with the development path.

Along this checklist, the Zambia 2007 DHS is most appropriate to analyze the effects of the drought with respect to short-term nutritional indicators. Between June 2005 and November 2005, Zambia suffered from a drought that occurred in the Western and Southern provinces and affected about 1,200,000 people (Guha-Saphir, 2018). For the Zambia 2007 DHS, interviews were conducted between April and October 2007. Table 1 provides an overview of the two datasets.

With respect to the characteristics of the datasets, a few adjustments are

[11] Details on the datasets and the specific criteria can be obtained from the respective webpages (The DHS Program 2018*a*; Guha-Saphir 2018).

necessary. DHS provides data only on the actual place of residence and on how long the respondent has been living in the household. Because the path, and the reasons for migration cannot be tracked, households that moved into the reported place of residence after the children were born are excluded. As outlined above, the prenatal period is equally important for a child's development and therefore the households are further restricted to be living in the reported region since nine months before the birth of their child.
In order to differentiate with respect to the before-after comparison in the DiD-setting, the dataset is further restricted to cover only children who are born before or during the drought. This cut also allows for a better comparison of the effects that require a longer timespan to be revealed.

3.2 Explained Variables

The World Health Organization (2010) established growth charts to compare the development of a child. These are the height for age, weight for age, and weight for height Z-scores (HAZ, WAZ, WHZ) and they indicate whether a child suffers from stunting, underweight, or wasting respectively, each defined as minus two standard deviations below the WHO Child Growth Standards (World Health Organization, 2010, p.1). Stunting is used as an indicator for adverse long-term influences. The indicator for underweight is influenced by both short- and long-term effects, while wasting indicates acute nutritional impairments. In order to analyze the effects of a drought that took place nearly two years prior to the interview period, the HAZ score seems most suitable for the analysis and the WAZ score is included to serve as an additional control. The WHZ score is not included, as wasting is not reported age-specific and cannot be aligned along the pathway of child growth, as is outlined in Rieger and Trommlerová (2016).
Figure 1 shows the weighted local polynomial smooths of the height for age and weight for age Z-scores.[12] Both, HAZ and WAZ, show distinct courses with respect to the age of a child, which are confirmed by Shrimpton et al. (2001), De Onis and Blössner (2003) and Rieger and Trommlerová (2016). In the Zambian population, the HAZ is declining until the age of 23 months and stays fairly constant thereafter. The kink slightly deviates from Rieger

[12]The figures present a local polynomial smooth. They were plotted with the *lpoly* command in STATA 13. All polynomial smooths are of degree three with an epanechnikov kernel.

and Trommlerová's estimated "structural break" of 18 months for the sub-saharan region, but in general the results are in line with the previous estimation (Rieger and Trommlerová, 2016, p.250, 255).[13]
The WAZ-profile shows a similar course, declining until an age of 23 months, so that the structural break can be applied in the same manner (cf. Figure 1).

3.3 Explanatory Variables

The literature unveils that the development of a child is influenced by various factors at the child-, mother-, household- and country-level. In line with the previous explanations and especially with the thorough analysis of growth faltering in Rieger and Trommlerová (2016), controls for facets at the child-, mother- and household-level are included. The chosen variables are shown in Table 2.
The estimation sample includes 2,302 children, with 4.3% of them being born in the affected regions during the shock. The mean age is 37.275 months and 49% of the children are male. They are 1.977, respectively .976, standard deviations below their age-specific height and weight. On average, a mother is 30 years old, 85.5% of the included mothers have at least primary education, 20.6% have secondary or higher education, and slightly more than 50% belong to the two poorest wealth quintiles. 25.5% live in an urban place of residence, 10.4% have access to electricity and 58.1% have visited a health centre in the last twelve months, but only 24.9% of the children ever received any vaccination.
Figure 2 shows that whether a child was born in the affected region significantly influenced the child's growth path. Although the children in the affected region score, in general, higher on the HAZ-profile, and partly on the WAZ-profile, distinct drops are observable around the age of 20 months - the time interval of the drought - which gives a first hint on the adverse effect of the drought and provides the setting to apply a differences-in-differences analysis.
Furthermore, maternal and household characteristics do affect child growth. Figure 3 and Figure 4 depict that higher wealth levels and a higher education status protect child growth. As reported in Figure 5, children living

[13] The term "structural break" is defined "as the age with the lowest weighted average value of HAZ" (Rieger and Trommlerová, 2016, p.249).

in an urban setting score higher on both nutritional and growth indicators. On the other hand, the effects of gender and vaccination status, reported in Figure 6, respectively Figure 7, are not clearly distinguishable.

4 Estimation strategy

While Rieger and Trommlerová (2016) analyze age specific correlates of child growth, Fuentes-Nieva and Seck (2010) estimate the effects of shock exposure on child growth via differences-in-differences.[14] Combining both approaches allows to refine the model in Fuentes-Nieva and Seck (2010) by considering the specific path of child growth in the estimation of shock exposure.

The aforementioned distinct drop in the HAZ- and WAZ-profile around the time of the drought for the group born in the affected region provides an appropriate setting for a DID estimation. This estimation requires a treatment variable D, with $d \in \{0, 1\}$, measured at two time periods T, so that $t \in \{0, 1\}$ (Lechner, 2011, p.174). The treatment variable indicates whether a child was born in a region affected by the shock (ar), denoted by $d = ar = 1$ if the child was born in an affected region, and 0 otherwise. Because the dataset is cross-sectional, synthetic time periods needed to be constructed for the DiD-estimation. The two time periods are split to cover the time before the drought took place and the time during the shock (bn), so that $t = bn = 1$ if the child was born during the shock, and 0 otherwise. Children that were born after the shock were not included.

The estimation with DID, and later with fixed-effects, requires the common trend assumption to be fulfilled (Angrist and Pischke, 2008, p.227-233,243; Lechner, 2011, p.174-175; Verbeek, 2017, p.388-390). This means that, apart from the effects of treatment, both the group born in the affected region and the one born in the unaffected region need to follow a common trend with respect to child growth. As outlined in Shrimpton et al. (2001), De Onis and Blössner (2003) and Rieger and Trommlerová (2016), child growth follows a specific pathway that shows similar traits in a worldwide comparison, which is sufficient to fulfil the common trend assumption.

[14] Rieger and Trommlerová (2016) account for shock exposure, but only by including a dummy for shock exposure in the survey year and only for the whole country. Therefore, only short-term effects can be captured by this strategy and regional variations are not taken into account.

The DID estimation leads to the baseline econometric model:

$$Y_i = \alpha_i + \beta_1 ar_i + \beta_2 bn_i + \beta_3 (bn \times ar) + \mathbf{x}\gamma + \varepsilon_i, \tag{1}$$

where Y_i is an outcome variable for child i, $\mathbf{x}$ denotes a vector of variables to control for specific child-, mother- and household-characteristics, and ε_i represents a simple error term. β_3 is the parameter of interest, measuring the impact of the Zambian drought on the affected population born during the shock.

Different to the paper by Fuentes-Nieva and Seck (2010), here, Y_i is continuous and the effects of shocks on growth and nutritional indicators are not estimated by employing a linear probability model. The estimation with the linear probability model when relying on various non-dichotomous variables, has significant shortcomings with respect to the analysis and the ease of interpreting the results (Ai and Norton, 2003). The same applies to the estimation by logit or probit in a DID-setting. Hence, the approach makes use of the underlying variables for stunting and underweight, namely the HAZ and WAZ scores. These variables are continuous and the effects can be estimated via ordinary least squares.

Equation 1 provides the baseline model for the estimation strategy which is further specified to account for the characteristics of the height for age, respectively weight for age profiles, which are shown in Figure 1.

Therefore, the baseline model is extended to take into account the "structural break" at 23 months as well as the interaction of a child's age with the specified control variables. The structural break is coded as a dummy variable, $sbreak = 1\ if\ childage > 23$, and 0 otherwise, and the control variables interact with $sbreak$ in order to account for changes after the decline in the HAZ-profile:

$$\begin{aligned} HAZ_i = \alpha_i + \beta_1 ar_i + \beta_2 bn_i + \beta_3 (bn_i \times ar_i) + \mathbf{x}\gamma \\ + \beta_4 childage_i + \beta_5 sbreak_i + \beta_6 (sbreak_i \times childage_i) \\ + \beta_7 (childage_i \times \mathbf{x}\gamma) + \beta_8 (sbreak_i \times \mathbf{x}\gamma) \\ + \beta_9 (sbreak_i \times childage_i) \times \mathbf{x}\gamma + \varepsilon_i, \end{aligned} \tag{2}$$

The WAZ-profile shows a similar course, so *sbreak* can be applied in the same form as above:

$$\begin{aligned}WAZ_i = \alpha_i + \beta_1 ar_i + \beta_2 bn_i + \beta_3(bn_i \times ar_i) + \mathbf{x}\gamma \\ +\beta_4 childage_i + \beta_5 sbreak_i + \beta_6(sbreak_i \times childage_i) \\ +\beta_7(childage_i \times \mathbf{x}\gamma) + \beta_8(sbreak_i \times \mathbf{x}\gamma) \\ +\beta_9(sbreak_i \times childage_i) \times \mathbf{x}\gamma + \varepsilon_i,\end{aligned} \tag{3}$$

Employing a "logarithmic function of age" for the WAZ profile is suggested by Rieger and Trommlerová (2016, p.248), which results in the following estimation strategy. This estimation is conducted to verify the robustness of the results:

$$\begin{aligned}WAZ_i = \alpha_i + \beta_1 ar_i + \beta_2 bn_i + \beta_3(bn_i \times ar_i) + \mathbf{x}\gamma \\ +\beta_4 log(childage_i) + \beta_7(log(childage_i) \times \mathbf{x}\gamma) + \varepsilon_i,\end{aligned} \tag{4}$$

The sample design of the Zambia 2007 DHS employs clustering and provinces are stratified in rural and urban parts (Central Statistical Office (CSO), 2009*a*, p.7-8). Sampling weights are used to adjust the data to represent the overall population (The DHS Program 2018*b*; Rutstein and Rojas, 2006, p.12-13). The estimation needs to account for these characteristics in order to avoid a bias of the results (Sturgis, 2004).[15]

Child growth is significantly influenced by household, and even more by maternal characteristics. Although some of them are observable and captured in the presented econometric models, another part of them is unobservable. Given that children who were born before or during the shock, live together in the same household, respectively belong to the same mother, allows to control for time invariant factors. Therefore, fixed effects at the household or mother level are applied to further check the robustness of the estimation. Likewise, the common trend assumption holds for both household and mother fixed effects (Wooldridge, 2008, p.494-496).

[15] Stata 13 offers the *svyset*-command to control for sampling weights, clustering and stratification and adjusts the estimation to consider the sample design, which is applied in the above setting (StataCorp, 2013, p.2-21,65-72).

5 Results

The findings indicate a significant impairment in the long-term growth of exposed children, although the results for fixed effects and the estimations for the WAZ are insignificant. Table 3 shows the results for the estimations of the height for age and weight for age Z-scores.

In this sample, the basic estimation, respectively mother and household fixed effects, yield that being exposed to the drought indicates that child height is .563, .561, and respectively .452, standard deviations below the age-specific mean. While the result is significant at the 1%-level in the basic setting, applying mother and household fixed effects yields only insignificant results. Although shock exposure lowers the age-specific weight by .163, .101, and respectively .186 standard deviations, the estimations for weight provide only insignificant results. Also, when applying a logarithmic function of age for the WAZ profile, the results are insignificant. Here, in the basic setting and when controlling for household fixed effects, age-specific child weight is indicated to be .202 and .147 standard deviations lower for those exposed. On the other hand, applying fixed effects at the side of the mother results in an implausible finding of an increase of .0298 standard deviations for the age-specific weight.

Though most of the estimations provide insignificant results, at least the coefficients point in the expected direction that shock exposure adversely affects child health. The significant estimation for the HAZ score in the basic OLS setting is a strong indicator for the lasting effects of shock exposure on child growth.

The insignificant results that are obtained when applying fixed effects seem due to the characteristics of this estimator combined with the traits of the dataset. Fixed effects rely on the within estimation in the particular group and therefore several variation is removed from the sample (Angrist and Pischke, 2008, p.226-227; Verbeek, 2017, p.386-388). The impact of the shock is mainly transmitted via household and mother specific channels that influence the child's growth path. When applying fixed effects at the side of the household or the mother, the significance decreases and the estimation provides insignificant results.

The WAZ score is used as an indicator for under-, respectively overweight, hence it can provide information on both short- and long-term effects. Al-

though impairments could have been observed during the drought, these adverse effects might be compensated in the timespan until the time of the interview. Children in the affected region score, in general, higher on the HAZ-profile, and partly on the WAZ-profile, as is shown in Figure 2, which indicates an improved health status in these regions. Therefore, the shock might be compensated and the estimation provides only insignificant results. Some characteristics of the employed datasets further influence the results. Issues arise concerning the patterns of migration (Fuentes-Nieva and Seck, 2010, p.165). Restricting the dataset according to the patterns of migration, might give rise to a twofold migration issue (Drabo and Mbaye, 2015): (1) Wealthy households are more flexible to relocate in order to improve their living conditions. As households with improved resources to cope with negative shocks are missing in the sample, the regression overestimates the effect of the drought. (2) Poor and poorest households are forced to leave their places of residence and because the most vulnerable households are missing, the analysis suffers from underestimation. In the presented case, migrated households have higher education and wealth levels and these differences are statistically significant. Thus, the regression likely overestimates the effect of the drought in Zambia.
The precision level of the EM-DAT further restricts the quality of this analysis (Guha-Saphir, 2018). Affected locations are only provided at the level of provinces, albeit it can be assumed that people close to border regions might be misspecified, because shocks may affect people across the reported borders. The assignment to either treatment or control group at border regions can be regarded as a measurement error in an explanatory variable and this affects the results in one of two ways (Wooldridge, 2008, p.318-320, Verbeek, 2017, p.144-146): (1) The measurement error is not correlated with the observed variables of region of residence, which would results in a still unbiased estimation, but along with increased variance. (2) If the classical errors-in-variables assumption holds, meaning that the measurement error is not correlated with the unobserved variable of shock exposure, the estimation itself will be inconsistent and suffer from attenuation bias. Given the datasets, shock exposure cannot be assigned with higher precision. Otherwise, it has to be taken into account that the population near border regions constitutes only a small amount of the overall population, thus the effect of the measurement error is rather small. With respect to the purpose

of this thesis, the main interest in the estimation is the direction and the significance-level of shock exposure on the respective health indicators.

6 Conclusion

Developing countries face a high burden of disease and are limited on their growth path. Shocks, including natural disasters, have further adverse effects of growth in the short- and the long-run. This thesis analyzes effects that natural disasters have on child health. The setting is provided by a drought that affected about 1.2 million people in two regions in Zambia during the year 2005. A demographic and health survey is employed and the indicators of interest are the WHO height for age and weight for age Z-scores (HAZ, WAZ), which are measured two years after the shock took place. The estimation strategy combines a DID approach with additional specifications to account for the age-specific growth path of children. The findings indicate a significant impairment in the long-term growth of exposed children, although the results for fixed effects and the estimations for the WAZ are insignificant.

This thesis supports the literature on the adverse effects of natural disasters on health indicators. Especially the adverse effects on the height for age profile, hence the increased risk of child stunting, are indicators for persistent and long-term interference of the individuals' development. With respect to the socioeconomic impairments that might result at several levels, implications for development policy are necessary along the lines of Dupas (2011). Preventive and remedial investments and measures are crucial to support the development of an individual over the lifetime. According to Bhutta et al. (2013), especially vitamin supplementation at various stages in the early stages of life seems to be an efficient way to enhance health care.

The synthetic DID estimation, relying on a cross-sectional dataset, can be used as a valid tool to circumvent issues of limited availability of more suitable datasets. Nonetheless, particularly panel data are needed to increase the validity of related studies in the future. Even more, the outcomes of preventive and remedial health investments can be analyzed more precisely so that cost-efficient solutions can be found to further improve the provision of health care. Increasing the precision level of the disaster databank is another way to improve the outcome of research and to target measures to the places where they are needed.

Figures and Tables

Table 1: Data on the drought and on the DHS

Country	Time of Disaster	Affected Regions	Number of affected Regions	Time of Survey	Sample Size
Zambia	06.-11. 2005	Southern, Western provinces	1,200,000	04.-10. 2007	6,401

Information on the disaster were obtained from EM-DAT (Guha-Saphir, 2018). The time of the survey and the sample size are reflective of the 2007 DHS of Zambia (Central Statistical Office (CSO), 2009*b*; The DHS Program 2018*a*).

cont.

Table 2: Summary statistics (Estimation sample)

Variable	Mean	Std. Dev.	Minimum	Maximum	N
hta	-1.977	1.559	-5.9	5.61	2302
wta	-0.976	1.073	-4.44	4.97	2302
bn	0.189	0.392	0	1	2302
ar	0.222	0.415	0	1	2302
bnar	0.043	0.204	0	1	2302
childage	37.275	11.536	17	59	2302
sbreak	0.853	0.354	0	1	2302
male	0.49	0.5	0	1	2302
totchrbn	4.599	2.476	1	15	2302
breastfd	20.129	4.917	0	50	2302
resht	157.704	6.652	107.1	196.7	2302
resage	30.03	6.744	16	49	2302
noeduc	0.145	0.352	0	1	2302
prmryeduc	0.649	0.477	0	1	2302
seceduc	0.189	0.391	0	1	2302
hghreduc	0.017	0.131	0	1	2302
prst	0.253	0.435	0	1	2302
poorer	0.248	0.432	0	1	2302
mddl	0.232	0.422	0	1	2302
rchr	0.177	0.382	0	1	2302
rchst	0.091	0.287	0	1	2302
urban	0.255	0.436	0	1	2302
electricity	0.104	0.306	0	1	2302
hlthcntr	0.581	0.493	0	1	2302
vaccination	0.249	0.432	0	1	2302

hta and *wta* depict the child's height for age, respectively weight for age score. *bn* and *ar* indicate whether a child was born during the shock, respectively born in the affected region and *bnar* constitutes the interaction of both terms. *childage* presents a child's age, measured in months, *sbreak* indicates whether or not a child is older than 23 months, and *male* is a dummy for male sex. The total number of children the mother has given birth to is reported in *totchrbn*. *breastfd* sums how many months a child was breastfed. *resht* and *resage* state the mother's height in centimetres and her age in years. The mother's education level is captured in *noeduc*, *prmryeduc*, *seceduc* and *hghreduc*, reporting whether a mother has no, primary, secondary or higher education. The wealth level of a family is categorised along five wealth quintiles and *prst*, *poorer*, *mddl*, *richer*, respectively *rchst*, depict whether they belong to the poorest, poorer, middle, richer or richest quintile. *urban* indicates whether the respondent lives in an urban setting. *electricity* is an indicator for electricity in the household. *hlthcntr* captures whether a child has visited a health facility in the twelve months prior to the interview and *vaccination* depicts whether a child has received at least one vaccination.

Table 3: Results of the regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	HAZ	WAZ	Log WAZ	M-FE HAZ	M-FE WAZ	M-FE Log WAZ	H-FE HAZ	H-FE WAZ	H-FE Log WAZ
bn	0.245	0.0608	-0.0613	0.291	0.351	0.125	0.257	0.292	0.179
	(1.37)	(0.47)	(-0.63)	(0.91)	(1.56)	(0.76)	(0.82)	(1.31)	(1.10)
ar	0.800***	0.0837	0.0833	0	0	0	0	0	0
	(5.04)	(0.69)	(0.69)	(.)	(.)	(.)	(.)	(.)	(.)
bnar	-0.563**	-0.163	-0.202	-0.561	-0.101	0.0298	-0.452	-0.186	-0.147
	(-2.67)	(-1.17)	(-1.48)	(-1.50)	(-0.38)	(0.12)	(-1.22)	(-0.71)	(-0.60)
male	-1.346	-2.706	-0.535	7.119*	2.641	0.0299	3.316	-0.399	-0.152
	(-0.60)	(-1.66)	(-1.02)	(2.01)	(1.06)	(0.03)	(0.87)	(-0.15)	(-0.18)
totchrbn	0.287	-0.0820	0.0403	0		0	1.029	-0.472	0.0312
	(0.41)	(-0.14)	(0.18)	(.)		(.)	(0.69)	(-0.44)	(0.11)
breastfd	-0.369	0.268	-0.0907	-1.339*	-0.576	-0.0150	-1.102	-0.244	0.00896
	(-1.23)	(1.56)	(-1.52)	(-2.29)	(-1.40)	(-0.18)	(-1.72)	(-0.54)	(0.11)
resht	0.132	0.0869	0.0607	0	0	0	-0.0321	-0.181	0.0618
	(0.93)	(0.76)	(1.37)	(.)	(.)	(.)	(-0.11)	(-0.88)	(1.15)
resage	-0.204	-0.119	-0.00369	0	0	0	-0.232	0.0895	-0.0398
	(-0.69)	(-0.49)	(-0.05)	(.)	(.)	(.)	(-0.35)	(0.19)	(-0.37)
educlv	-2.416	-2.949*	-0.264	0	0	0	-0.286	-1.628	0.0731
	(-1.31)	(-2.52)	(-0.54)	(.)	(.)	(.)	(-0.07)	(-0.56)	(0.12)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	HAZ	WAZ	Log WAZ	M-FE HAZ	M-FE WAZ	M-FE Log WAZ	H-FE HAZ	H-FE WAZ	H-FE Log WAZ
wealth	0.191	0.497	0.300	0	0	0	0	0	0
	(0.15)	(0.58)	(1.09)	(.)	(.)	(.)	(.)	(.)	(.)
urban	-0.737	-0.281	-0.196	0	0	0	0	0	0
	(-1.63)	(-0.71)	(-0.23)	(.)	(.)	(.)	(.)	(.)	(.)
electricity	1.829	3.204	-1.649	0	0	0	0	0	0
	(0.37)	(1.25)	(-1.33)	(.)	(.)	(.)	(.)	(.)	(.)
hlthcntr	-1.976	-1.200	-0.487	0	0	0	0.403	-0.960	-0.949
	(-0.90)	(-0.77)	(-0.99)	(.)	(.)	(.)	(0.10)	(-0.35)	(-1.26)
vaccination	-4.840	1.811	1.487*	-3.485	4.241	-0.553	-2.240	4.900	-0.108
	(-1.92)	(0.83)	(2.27)	(-0.71)	(1.23)	(-0.59)	(-0.40)	(1.21)	(-0.11)
N	2302	2302	2302	2302	2302	2302	2302	2302	2302
R^2	0.126	0.106	0.095	0.163	0.083	0.054	0.168	0.129	0.093

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The table reports the estimation outcomes for the HAZ- and both WAZ-profiles, as provided in Section 5. Also, the outcomes of applying fixed effects at the side of the mother (M-FE) and at the household level (H-FE) are shown. The included variables are explained in more detail in the notes of Table 2.

The estimations follow the strategies outlined in Section 4. The effects of a child's age, sbreak, the respective interaction terms and of the controls for the region and for the time of the interview are not shown in the table. The fixed effects estimation removes several variation from the sample and the affected variables are reported as (.). Their interactions with the age-related variables are not included.

Columns (1) to (3) show the results for the baseline estimation, which are adjusted to be reflective of the sample design. The standard errors are clustered at the primary sampling unit and the estimation accounts for stratification and sampling weights. Further remarks are provided in Section 4.

Figure 1: Age profiles of HAZ and WAZ score

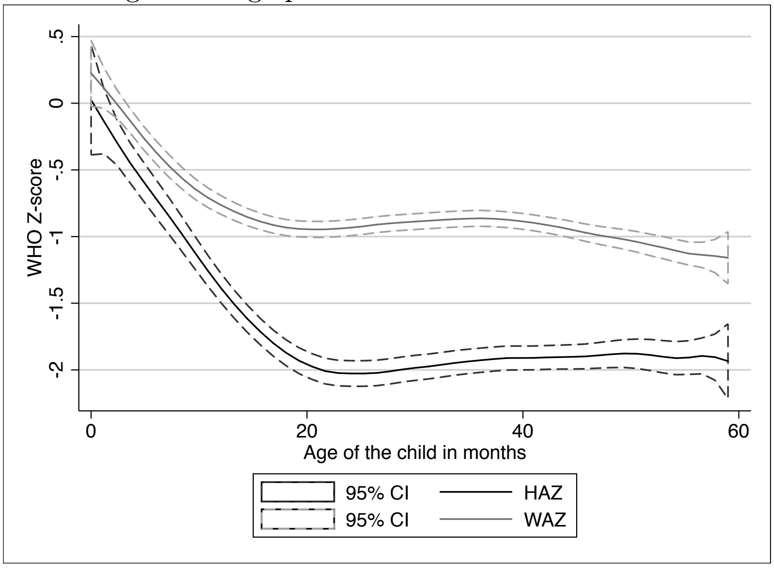

Figure 1: Age profiles of HAZ and WAZ score according to the WHO child growth standards. Weighted polynomial smooths. Dashed lines are reflective of the 95% confidence intervals.

cont.

Figure 2: Age profiles by region

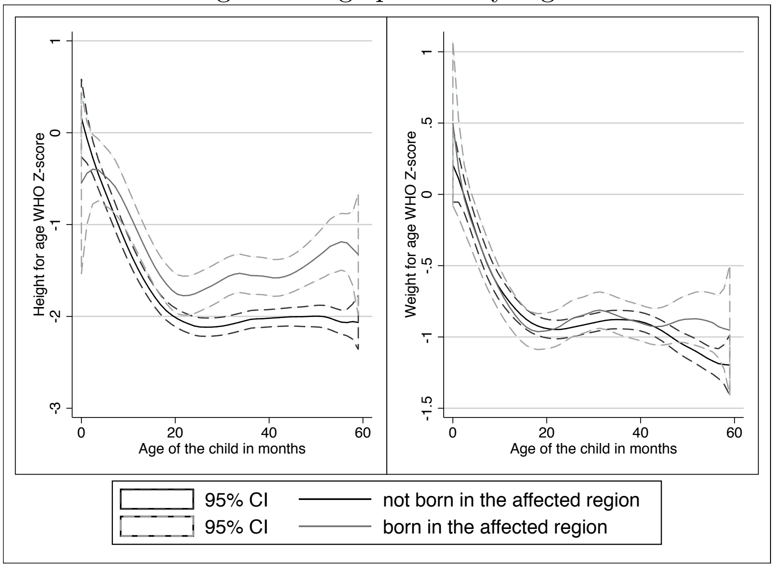

Figure 2: Age profiles by region. Weighted polynomial smooths. Dashed lines are reflective of the 95% confidence intervals.

Figure 3: Age profiles by wealth quintiles

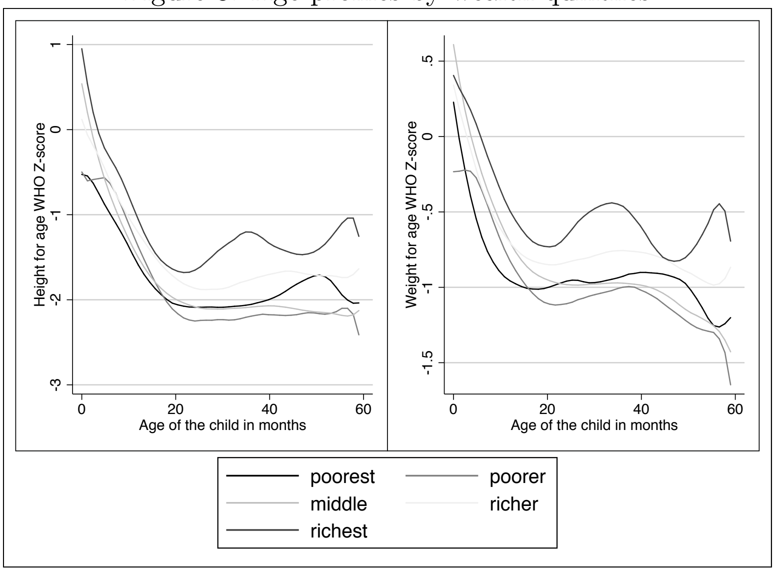

Figure 3: Age profiles by wealth quintiles. Weighted polynomial smooths. Confidence intervals are not included for reasons of visibility.

Figure 4: Age profiles by the mother's education level

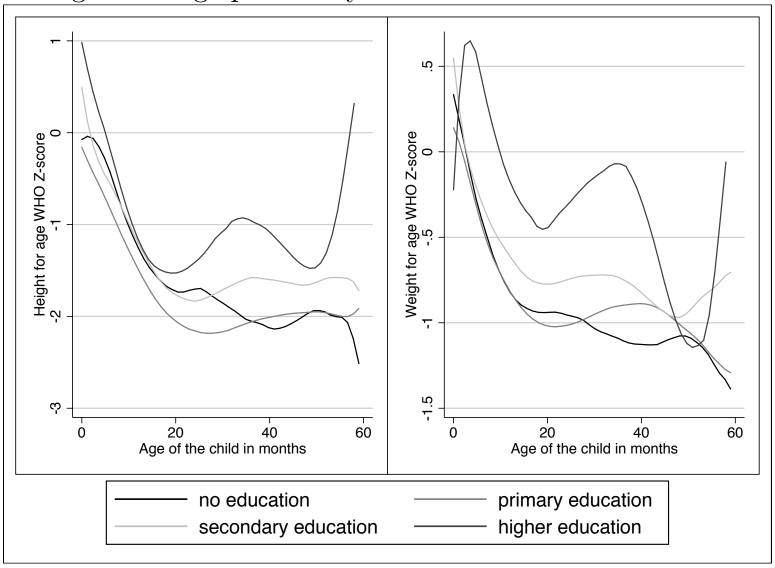

Figure 4: Age profiles by the mother's education level. Weighted polynomial smooths. Confidence intervals are not included for reasons of visibility.

Figure 5: Age profiles by place of residence

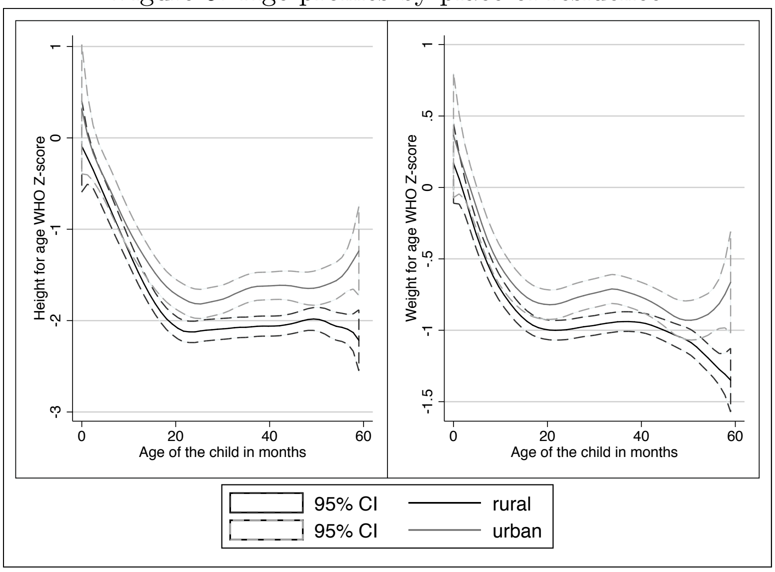

Figure 5: Age profiles by place of residence. Weighted polynomial smooths. Dashed lines are reflective of the 95% confidence intervals.

Figure 6: Age profiles by gender

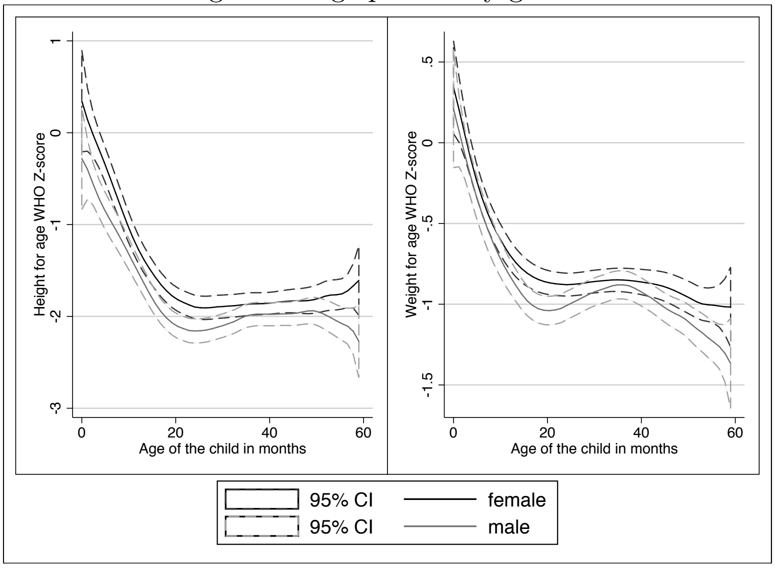

Figure 6: Age profiles by gender. Weighted polynomial smooths. Dashed lines are reflective of the 95% confidence intervals.

Figure 7: Age profiles by vaccination status

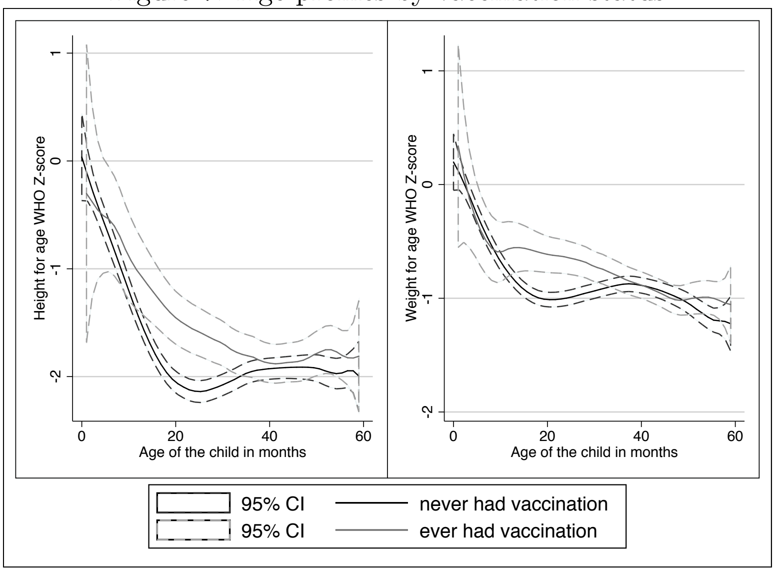

Figure 7: Age profiles by vaccination status. Weighted polynomial smooths. Dashed lines are reflective of the 95% confidence intervals.

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