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Examining the link between food prices and food insecurity: A multi-level analysis of maize price and birthweight in Kenya

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ABSTRACT

In developing countries where many poor people rely on rainfed, locally produced food for the majority of their caloric intake, shifts in climate and weather patterns can dramatically reduce agricultural productivity. The reduction in agricultural productivity reduces overall food availability and ultimately impacts food accessibility, putting millions of people at risk for malnutrition. In this project we focus on Kenya where roughly a third of households are food insecure. We examine the relationship of the price of maize and low birth weight to help quantify the impact of local food prices on one outcome of household food insecurity. Using spatially referenced data from recent Kenyan Demographic and Health Survey datasets, price data, livelihood information, and a remotely sensed-based measure of local growing season productivity, we develop a dataset linking pregnancies occurring from 2001 to 2008 to the spatially and temporally relevant maize price data. We construct several regression models to examine the impact of local maize prices and remotely sensed based estimates of crop production on infant birth weight – specifically low birth weight. The results of the models highlight the importance of including community crop production to evaluate maize price impacts on low birth weight outcomes. Also, because of the positive correlation between pre-pregnancy maize prices and birth weight, the results suggest that some households may benefit from high prices or that high prices may impact the number of conceptions. More generally, our work demonstrates that multilevel models that account for community-level variation are important for disentangling these complex relationships and can contribute to the discussion of how to design more effective food policies.

Introduction

"Food security exists when all people, at all times, have physical and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life" (World Food Summit, 1996). Episodes of household food insecurity occur when access to food decreases (e.g. cost increases while income or entitlements do not), when food availability decreases (e.g. crop production decreases) or when there are constraints to people's proper use of calories (e.g. due to illness or lack of nutritional knowledge).

In developing countries where many poor people rely on rainfed, locally produced food for the majority of their caloric intake, shifts in climate and weather patterns can dramatically reduce agricultural productivity. This reduction in productivity reduces overall food availability, increases local food prices due to rising demand and diminished supply. This ultimately impacts food accessibility, putting millions of people at risk for malnutrition (Sen, 1990). Given this frequently adopted model of food security, policy professionals and aid programs monitor the local pricing of staple crops as an indicator of impending food crises. In an effort to improve scientific understanding of food insecurity and evaluate the usefulness of pricing data as an indicator of food insecurity, we examine the link between price and household health outcomes related to food insecurity – specifically the weight of an infant at birth.

In this project we focus on Kenya where roughly 1/3 of households are food insecure (Bloss et al., 2004; FAO, 2009) and dependence on rainfed agriculture to produce affordable food is high. Given the potential for crop losses owing to frequent and increasing drought conditions (Williams and Funk, 2010), interest in food prices as a measure of access to food or indications of potential food stress is growing. Considering the Kenyan climate conditions

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and within the framework of the dominant food insecurity theoretical models (as highlighted above), we anticipate that episodes of household food insecurity may increase, leading to an increase in low birth weight (LBW) babies.

Here we examine the relationship between food prices and household food insecurity. The price of maize, a major Kenyan food staple, serves as an indication of fluctuations in food access, while LBW represents household food insecurity. We combine data from four separate data types/sources to conduct this analysis – spatially referenced parental and infant information from the most recent Kenyan Demographic and Health Surveys (DHS), monthly maize prices, livelihood classifications, and a local measure of growing season productivity. Each pregnancy recorded in the DHS that resulted in a live birth (and where birth weight was measured) is temporally and spatially linked to maize price and environmental conditions relevant to the most recent growing season. Using this linked dataset we can determine how and whether local maize prices, an indicator of food accessibility, is linked to LBW.

Background

Low birth weight

When babies are born weighing less than 2500 g, the international standard for low birth weight (LBW), their mortality rates are higher than those of their normal birth weight counterparts (Walker et al., 2007). If an LBW baby does survive, her future is grimmer than that of a normal birth weight baby. Educational rates and income levels are lower among children who are born with LBW and if a mother was herself characterized as LBW then she is more likely to produce LBW children (especially girls) (Victora et al., 2008). LBW babies are therefore less likely to grow into healthy and economically productive members of society.

The weight of an infant at birth is the result of a multitude of interrelated biological (e.g. maternal height) and socio-environmental (e.g. socioeconomic status, health care, maternal age, time since previous birth) factors (Mwabu, 2008; Abu-Saad and Frasier, 2010; also see Kramer, 1987 for an extensive discussion). Among the most prominent of the environmental factors, is maternal nutrition (Kramer, 1987; Keen et al., 2003; Wu et al., 2004; Cetin et al., 2010). Studies of interventions related to maternal nutrition have produced a variety of results identifying the impacts of different types of vitamins, minerals and eating habits on the birth weight of a newborn. Intervention efforts to improve birth outcomes, including LBW, have historically focused on the third trimester as the period where maternal nutrition is of prime importance. More recent studies (of humans and animals) have highlighted the importance of the earlier stages of pregnancy and even pre-pregnancy, on birth outcomes (Moore et al., 2004; Cucó et al., 2006; Rao et al. 2001; Abu-Saad and Frasier, 2010). And while results of successful interventions are not always consistent across human studies, the positive influence of maternal nutrition on the birth weight of an infant in animal studies is undeniable (Wu et al., 2004).

One component of maternal nutrition relevant in a food insecure context is appropriate caloric intake and weight gain, which are directly linked to food availability and accessibility. Therefore, while LBW is an indicator of future health of the child it is also represents nutritional deficiencies of the mother (Young, 2001). In highly food insecure communities – where adequate food supply is limited or food is costly (see the UNICEF framework, 1990) – the potential for women to intake an adequate amount of nutritional food is unlikely, and could possibly increasing the risk of a woman delivering an LBW baby (Young, 2001). We therefore theorize that women who have the least access to food or experience reduced access to food (price increases would reduce access) would not gain the proper amount of weight or consume the needed calories for healthy in-utero growth, resulting in a LBW infant. Based on previous studies, the impacts of reduced food access at any point in pregnancy and possibly even during the pre-pregnancy period could have a negative impact on birth weight.

Linking LBW and food insecurity in Kenya

For this analysis, we rely on the Food and Agriculture Organization's (FAO) model of household food insecurity. As reflected in the definition above, this model ties food security to four primary factors– access, availability, utilization and stability (UNICEF, 1990; Devereux, 2001a; FAO, 2012. These determinants (with some variation) of food insecurity have been thoroughly examined in the literature with the "access" component generally determined to be of particular importance (Sen, 1981; Sen, 1997; Smith et al., 2000 and Devereux, 2001b). Price of food serves as one measure of access.

In developing countries poor people generally spend about 75% of their income on food (Darnton-Hill and Cogill, 2010). As food prices go up they are able to purchase less food. At first, a reduction in the diversity of food occurs followed by a reduction in the amount of basic food staples and water (Darnton-Hill and Cogill, 2010). Increases in the incidence of LBW as a result of increased food prices have been seen in history across the globe. Darnton-Hill and Cogill (2010) describe the findings of several studies: a food/economic crisis in Indonesia is correlated with an increase in negative health effects on babies who were conceived during the period (Block et al., 2004); an increase of LBW babies following an increase in the price of staple foods in the Congo (Martin-Prével et al., 2000); small negative effects on birth weight resulting from food rationing during the Dutch famine in the mid-20th century which were then followed by a future of negative health consequences where exposure to rationing during the third trimester (the last 3 months of pregnancy) was found to be of particularly importance (Stein and Susser, 1975).

We build on these prior studies and examine the impact of the price of maize, a staple of many Kenyans, on LBW. In Kenya one of the most common and least expensive food products is maize (Freeman et al., 2004; Grobler-Tanner, 2006). Maize provides at least 40% of the calorie requirements for around 96% of the Kenyan population (Byerlee and Eicher, 1997) and the poorest people may consume as much as 70% of their calories from a combination of maize and beans (Greer and Thornbeck, 1985). Depending on where in Kenya they are located, some households primarily grow their own maize while others rely on purchased maize from local markets (Freeman et al., 2004). Poor households can spend a quarter of their income on maize purchases which may increase given an increase in maize price.

If people cannot afford maize or their own maize crops do not grow then there may be little that is accessible to them and they may begin to show indications of reduced caloric intake – malnutrition. Because of the importance of maize in the diet of the Kenyan poor, the widespread use of maize prices by the FAO and the international community as an indication of potential food emergencies, as well as the availability of maize data, we focus specifically on the local prices of maize in several areas of Kenya. We theorize that if the cost of maize increases (indicating reduced access to a staple product) many of the poorest people will be deprived of a vital source of nutrition and will show signs of malnutrition.

However, while perhaps less researched, some households may also benefit from maize price increases if they are able to sell excess maize. Some reports have noted that maize sales constitute as much as 44% of a household's income (see Kimenju and Tschirley, 2008). Given, the complexity of the situation in Kenya, however, household income may increase with price increases

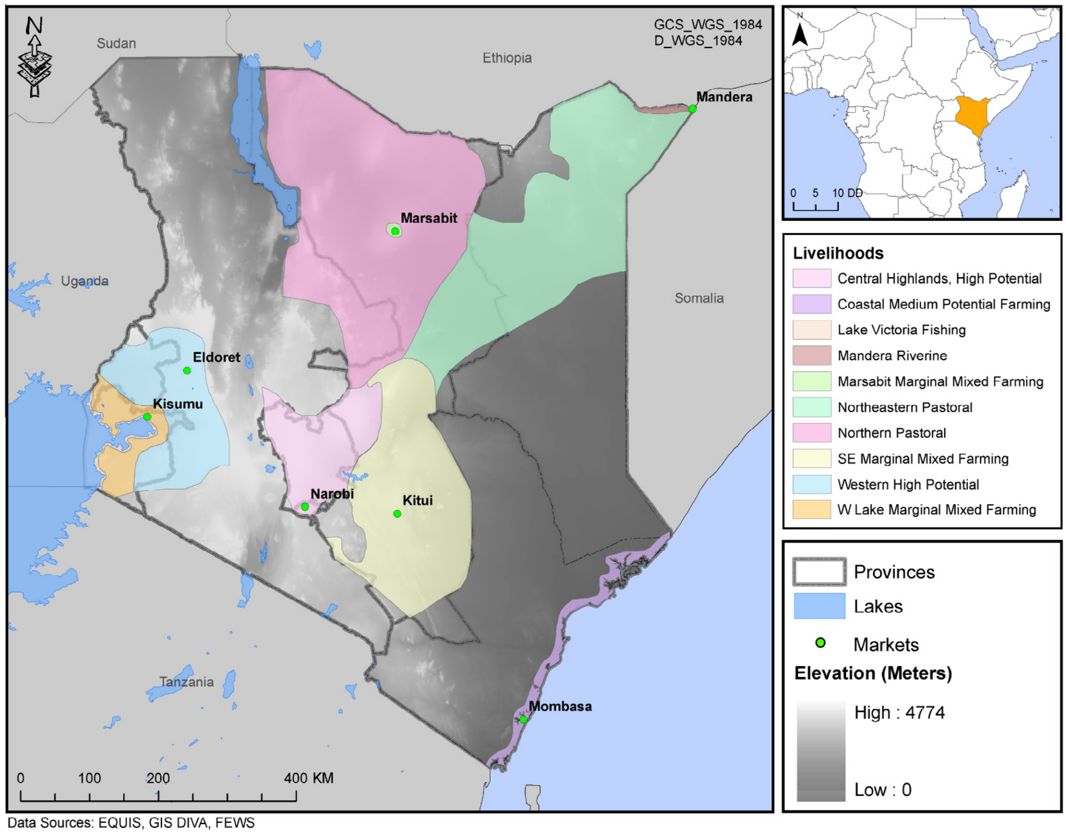

Fig. 1. Markets and livelihood zones in Kenya. *Note:* In our analysis we combined the Lake Victoria zone and the Lakeshore Marginal zone into a single zone. We also combined the very small zone around Marsabit with the larger surrounding pastoral zone and the Mandera Riverine zone with the Northeastern Pastoral zone. These zones were grouped because of the size of the zones and the small sample number of births in the zones. Livelihood reports indicated that they relied on the same major markets.

and may complicate a straightforward analysis of food prices and health outcomes.

In this project we account for the possibility that maize dependence may vary. Some households may primarily purchase their maize from the market while others may be less sensitive to high prices because they produce their own maize. Therefore the sensitivity to prices may vary according to the local dominant livelihood strategy. In Kenya, accounting for this variation in dependence may be particularly important because Kenya has populations that live in a highly productive agricultural zone – towards the middle of the country, near Lake Victoria and Nairobi – and by very hot and dry pastoral zones in the northeastern part of the country, near the Somali border. Furthermore, there are a number of areas that lie in the gradient between these two extremes where households grow crops or gardens and manage small herds of goats and cattle. These households within this gradient, or more marginal agricultural land, depend on seasonal rains to produce food for themselves and their animals (see Fig. 1). One of the particular challenges that Kenyans face is that precipitation is decreasing and temperatures are increasing (Funk et al., 2010; Williams and Funk, 2010) and droughts are becoming increasingly frequent. International commodity prices are also influential in these region, and these prices are at an all-time high (Brown et al., in press). Because local production and local prices are inversely related, as in many semi-arid agroecosystems in Africa (Brown et al., 2008), when there are regional food shortages concerns of reduced food accessibility for vulnerable individuals grows.

Data and measures

An infant's birth weight is the result of both biological and socio-environmental features. To use models to explain variation in LBW, with the specific goal of identifying the impact of reduced food access, we must incorporate a diverse set of factors related to an infant's biology, the socioeconomic characteristics of her mother and household, and factors related to food access. Therefore, to examine LBW we rely on three primary types of data – health, environmental/geographical and economic. The descriptions of the data and the measures calculated from each data source follow.

Health data and measures

The health information comes from the two most recent Demographic and Health Survey (DHS) datasets, 2008/09 and 2003. DHS data provide detailed health and population information for most of the poorest countries around the world. These cross-sectional, spatially referenced data (DHS provides the latitude and longitude values of their sampling clusters which contain about 10–20 households) contain detailed information about maternal characteristics and provide retrospective information about the health of infants including their birth weights. This data provides the micro-level health and socio-economic information used in the analysis.

We use information from the most recent birth[1] as recorded in the DHS. Each infant, with a recorded birth weight provided by the mother, is classified as LBW or no-LBW. This categorical LBW measure serves as the dependent variable. DHS data also provide information on length of time at current residence. We use this information to restrict the sample to only those households where the pregnancies occurred in the current area of residence. This restriction allows us to link past information to the relevant pregnancy. Without this restriction we may inappropriately attribute

[1] The interaction between pre-pregnancy price and NDVI was evaluated as well but was not significant in our analyses.

Table 1
Descriptive information for select variables used in the analysis.

Variables	The units or the level of the variables	Mean	Median	SD	Min.	Max.	Count
Independent variables							
Multiple/twin	Categorical variable, 1 if the child is a multiple birth and 0 if a singleton						1 = 32; 0 = 1868
Birth interval	Length of time, in months, between the current birth and the prior birth	48.34	39	30.66	10	245	1355
Birth order	Number of previously born children	2.87	2	1.9	1	12	1900
Child's sex	Categorical variable, 0 if the child is male and 1 if female						0 = 999; 1 = 901
Mother's age	Age of mother in years	26.7	25.83	6.32	13.92	45.67	1900
Mother's height	Height for age standard deviations from the reference median (as calculated by DHS)	−65.87	−69		−377	582	1860
Education	Highest level of education attended by the mother. Categorical variable with three levels						None/Primary = 1123; Secondary = 552; Higher = 225
Partner education	Highest level of education attended by the mother's partner. Categorical variable with four levels including the missing or "don't know" responses						Primary = 760; Secondary = 651; Higher = 290; no response = 190
Water source	Categorical variable for type of water source. 0 for piped, 1 for well water, 2 for surface/spring, 3 for other (includes bottled and rain water)						Piped = 934; Well = 413; Surface = 431; Other = 122
Floor	Categorical variable for type of flooring the residence. 0 for unfinished flooring (dirt, sand, dung, earth) and 1 for finished flooring (wood, carpet, cement, tile)						Unfinished = 797; Finished = 1103
Urban	Categorical variable for type of place of residence, 0 for urban and 1 for rural						Urban = 836; Rural = 1064
Birth month	Categorical variable for month of birth						Jan. = 135; Feb. = 128; March = 161; April = 172; May = 192; June = 173; July = 164; Aug. = 157; Sept. = 161; Oct. = 145; Nov. = 157; Dec. = 155
Birth year	Categorical variable for year of birth						2001 = 212; 2002 = 398; 2003 = 182; 2004 = 109; 2005 = 139; 2006 = 218; 2007 = 270; 2008 = 372
Pre-pregnancy price	The mean price of maize during the three months pre-pregnancy (including time of conception)adjusted for the livelihood zone (see text for discussion)	−0.01	−0.06	0.78	−1.84	4.05	
Average pregnancy price	The mean price of maize during the nine months of pregnancy adjusted for the livelihood zone (see text for discussion)	−0.07	−0.11	0.40	−0.89	1.37	
NDVI	Standardized NDVI, see text for more discussion						
Dependent variable							
Low Birth Weight	Categorical variable, 1 if the child weighs less than 2,500 grams at birth and 0 if otherwise						1 = 115; 0=1785

Note: SD = standard deviation; data are rounded up.

pregnancies with price or landscape information not reflective of the mother's actual experience. Unfortunately, DHS does not contain information on prior residence making it impossible to construct a full residential history or allow us to link women with information related to their prior place of residence.

We select a suite of explanatory variables from the DHS to control for variation in birth weight (see Table 1). We adjust for the child's sex as well as if the child is a twin (or triplet). Generally, male infants and multiples are smaller at birth than female infants and singletons. We also adjust for birth order and birth interval, with the assumption that children of higher birth order and those who were born within a short period of time following the preceding birth may be smaller than their counterparts (Seidman et al., 1988; Rutstein 2008b). There may be fewer food resources per person in a household with more children. Moreover, the mother's time for personal care may be limited by the increase in childrearing responsibilities that come with more children and children spaced close in age.

Mother's characteristics are also included as control factors. Mother's height is included because it reflects the mother's experience with food insecurity – mothers who were stunted as children are more likely to give birth to LBW infants (Young, 2001; Victora et al. 2008) and height, as opposed to other anthropometric measurements, is not subject to short term dietary changes in the mother (mother's current weight may not reflect her weight at the time of pregnancy). Maternal age is related to infant size as babies born to older women are more likely to weigh more than those born to younger women (Swamy et al., 2012; Seidman et al., 1988). Mothers' education is also included. More educated mothers may have greater access to health care, may have a greater understanding of nutritional requirements during pregnancy, and may also have greater social capital which may help to ensure a more healthy and less stressful pregnancy (see, for example, Caldwell, 1979 and Caldwell, 1994; Hobcraft, 1993).

With respect to household characteristics, floor material and partner educational attainment serve as a measure of household wealth or socio-economic status. We use these variables because household income information is not included[2] in the DHS. While, there is potential for some households to actually benefit from high

[2] (Rutstein, 2008a).

prices, namely, those households that are producers/sellers of maize (Jayne et al., 2000), these households are most likely to be wealthier, land-owning households. Therefore we assume that the poorest households, those with unfinished flooring and with the lowest level partner education, will be most negatively impacted by high food prices and are therefore more likely to experience LBW during times of food price increase. We include two variables to measure type of place of residence – urban or rural (as designated by the data collection organization) and a water source variable to differentiate the more isolated households from those that are urban or peri-urban/suburban. The most well-off and urban/peri-urban households are likely to have piped water, while more rural households will rely on well water or other water sources. We assume that urban/peri-urban households will have greater access to food markets and prenatal health care, which are both likely to impact the weight of a baby at birth. We also include birth month to capture any seasonality effects related to food availability and the time of birth. Finally, we incorporate birth year owing to the potential for political or environmental events that may have shifted country-level pricing or health outcomes that we have not accounted for (Mason et al., 2011).

Environmental/geographical data and measures

The livelihood zone data (Fig. 1) come from the US Agency for International Development's Famine Early Warning Systems Network's (FEWS NET) recent efforts to characterize the dominant livelihood strategies in a number of developing countries. With the use of local weather patterns, market information and expert knowledge, FEWS NET has constructed zones that characterize the dominant strategy used to produce money and food in a general area. The use of livelihood information serves a dual purpose: (1) We use the livelihood information to identify the dominant markets of the area and assume that the pricing of the dominant market reflects the general prices in a livelihood zone and (2) we incorporate the livelihood data into the analysis based on our assumption that individuals living within certain livelihood zones have a differential reliance on their local markets as discussed previously.

From the livelihood zone information (report found on FEWS.net) we can qualitatively classify each zone's dependence on purchased maize to inform our expectations about the impact of price increases. Communities within zones where there is a greater dependence on store-bought maize, for example, the Lake Victoria fishing zone, should have more sensitivity to price increases.

To capture local food production beyond that provided and market dependence at a micro-scale we use an additional geographic variable that provides a measure of "greenness" – normalized difference vegetation index (NDVI)[3] (Tucker, 1979), which has been shown to be related to primary productivity and leaf area of plants (Sellers, 1985; Townshend and Justice, 1986) and provide a way to measure directly the impact of moisture and temperature conditions on plant health. Vegetation indices are usually composed of red and near-infrared radiances or reflectances (Tucker, 1979), and are one of the most widely used remote sensing measurements (Cracknell, 2001). NDVI was first developed using hand-held radiometers, and its relationship with aboveground plant matter was established by correlating information from instruments to the weight of dried plant material in a grassland ecosystem (Fensholt et al., 2006; Karnieli et al., 2010). Vegetation indices can then be used as surrogate measures of vegetation activity, including crops, from field to continental scales and across multiple agroecosystems (de Beurs and Henebry, 2004; Funk and Budde, 2007). Unlike rainfall datasets, vegetation data is completely independent of ground observations. Its error structure is related to land cover, with more humid and tropical ecosystems having higher errors due to high amounts of atmospheric water vapor and clouds during the growing season (Brown, 2008). Drought-related food security problems are often in semi-arid and sub-tropical ecosystems with low to moderate errors in satellite-derived vegetation data (Morisette et al., 2004).

Here we use NDVI data from the MODIS instrument on the NASA Terra satellite (Huete et al., 2002; Justice et al., 1998). MODIS based NDVI has been collected since 2000, is available at 250-m resolution for all of Kenya and is available in 8 day increments (maximum values are taken over the preceding 10 days). In this analysis, we take the maximum NDVI value during the growing season of each year in a 10 km radius around each DHS sampling cluster and link it to the spatially and temporally relevant pregnancy. We then standardize[4] NDVI for use in the statistical analysis, as is common practice (subtracting the mean and dividing by the standard deviation over the entire set of observed NDVI values).

We anticipate that households where local NDVI values are high (i.e. an area where large amounts of vegetation are present) will generally be less reliant on markets for food, especially when price increases occur, as they may be able to either grow their own food or rely on very local food sources (neighbors, nearby family, etc.). In areas where crops are grown for sale (tea, coffee, and others) a high NDVI value may still indicate increased household income as a result of crop sales. Alternatively, people who live in areas where NDVI values are low are more likely to depend on the market for their maize. This use of NDVI provides us greater micro-level insight than is provided by the livelihood zones alone into probable dependence on the land for food.

Economic data and measures

The final type of data used in this analysis is economic data. The Kenya price data is derived from seven markets in Kenya: Mombasa, Nairobi, Eldoret, Kisumu, Kitui, Mandera and Marsabit. The data are from a continuously updated price database comprised of food prices from 232 markets in 39 countries, sourced from both the FAO and FEWS NET. The database has retail price data in local currencies from 1997 to 2011, but the starting year of each series varies by market. Here we use prices reported for maize from the seven markets. As explained previously, we are interested in maize because it is a staple crop. An additional benefit arises because the maize price information is the most complete time series as compared to other available cereals or products. No consistent, spatially-relevant estimates of inflation rates exist for Kenya, so instead of adjusting for inflation the data is standardized at the market-level (which is used to proxy all prices within the relevant livelihood zone) and we include dummy variables for year. The monthly data are then matched by the birth date of each baby in each of the relevant market areas (in our case livelihood zones serve as the "marketshed") in the sample to the 12 months preceding the birth. These standardized data are then averaged over two time periods for each individual observation; one time period corresponding to the pregnancy as well as the time period corresponding to the three months prior to the pregnancy.

[3] In related work by Brown et al. (2012), local NDVI values are only minimally related to large, regional markets like the ones used here. Because the pricing in large markets reflects international influences more than local production, we feel that it is appropriate to include both NDVI and regional price in a model examining access. As market prices may only be relevant when local production (local NDVI values) is low. Additionally, our preliminary analyses of price and NDVI data indicated no significant linear correlation between these measures.

[4] Also known as "normalized". We have simply calculated the mean and the variance over all observed NDVI values and subtracted the mean from each observation and divided by the standard deviation.

Methods

Given the hierarchical nature of the data, specifically due to the way the pricing data were standardized and an assumption of non-independence among those who live within the same livelihood zone, we use multilevel[5] models (Gelman 2006; Gelman and Hill 2006) to examine birth weights. Further, because the dependent variable (LBW) is a categorical variable we use a logistic multilevel model. Births are nested within livelihood zone. In other words, livelihood zone is treated as a random effect in the models while the other variables listed in Table 1 are treated as fixed effects. Variations in the local rate of inflation and potential unmeasured variation in factors related to pricing necessitate nesting individuals within geographic areas relevant to the markets (see Fig. 1). Significance of the estimated coefficients is based off of bootstrapping. Consistent with the data generating mechanism, the bootstrapping methodology, coded by the authors, incorporates the nested design of the data.

Results

Table 2 provides some specific quantitative descriptions of the data according to our livelihood zones – the areas that are spatially relevant to the pricing data. In the Northeastern Pastoral zone, where prices are comparatively higher and NDVI is low, 11% of all babies in our sample were classified as LBW. The Northern pastoral zone with high prices and low maximum NDVI values reports the next largest share of LBW (9%). In terms of education rates, frequently observed as a significant predictor of infant health including healthy weights at birth, we again see the northern areas of the country as distinct from the rest of the country. The two northerly zones report the lowest shares of secondary (or higher) educated mothers from our sample. The lush, highly cultivated zones, the Central Highlands and the Western High Potential zone, report the highest percentage of mothers with a secondary education – around half of the sample. Therefore, before further analysis, the zones in the northern part of the country stand apart from the rest of Kenya in terms of education, LBW and NDVI.

The regression models presented in Table 3 provide further insight into LBW in Kenya. We constructed several regression models to facilitate an analysis of the impact of local maize prices on infant birth weight – specifically LBW. In the first model we examine the relationship between standard maternal/infant covariates, NDVI, and the pricing variables and LBW. Among the control variables, the only significant variables in this model are related to biological factors, mother's height and twin/multiple status, and water source. Taller mothers are less likely to have LBW babies and singletons are also less likely to be LBW than twins/multiples. Women who live in households where the water comes from "other" sources (bottled, rainwater, trucks) are less likely to have low birth weight babies than those who rely on piped water, even after accounting for urban/rural residence. In terms of the variables central to this analysis, pre-pregnancy price is negative and significant ($p < 0.05$) – suggesting that an increase in price is related to reduced likelihood of low birth weight. In Model 1a we include the interaction between NDVI and the average price during pregnancy[6]. The interaction is positive and significant ($p < 0.05$) and the AIC indicates a slightly improved fit over Model 1.

Because of the complications involved we use the model to quantitatively estimate the likelihood of LBW. We keep the standardized NDVI value fixed at a low of −3.8 and calculate the likelihood of LBW over all values of the other independent variables. We then take an average of the predicted outcomes. The average marginal predicted probability of LBW at the fixed (standardized) NDVI value of −3.8 is 0.12 (with 50% of the predictions falling between 0.04 and 0.17). Using a much higher standardized NDVI value of 1.68, the average marginal predicted probability of LBW is 0.05 (with 50% of the predictions falling between 0.02 probability of LBW and 0.05 probability of LBW). To test the sensitivity to the fixed NDVI value we evaluate the first and third quartiles of NDVI (−0.43 and 0.69 respectively), we observe average marginal predicted probabilities of 0.06 (50% between 0.03, 0.07) and 0.05 (50% between 0.03 and 0.06). In evaluating the predicted probabilities for a low NDVI value and a low price value we observe some higher predictions of LBW than the average marginal values (probability of LBW as high as 0.6–0.8). As NDVI and price increase we see a decrease in the predicted LBW probability. We can therefore conclude that when NDVI is low, the likelihood of an LBW event is increased, even in the event of comparatively low maize prices during pregnancy.

Conducting the same average marginal predicted probability calculations based on Model 1a for price during pregnancy, we observe a much smaller difference between the lowest and highest observed prices. The lowest recorded (standardized) price experienced during pregnancy in our sample is −0.89 (standardized unit). The resulting average marginal predicted probability of LBW is 0.05 (where 50% of the predictions fall between 0.02 probability of LBW and 0.06 probability of LBW). For the highest price value of 1.36 (standardized unit) the average marginal predicted probability of LBW is 0.1 (where 50% of the predictions fall between 0.05 and 0.13).

For Models 2 and 2a, we repeat the general analysis of our first and second models but exclude first (live) births and include the preceding birth interval (i.e. spacing between children). Preceding birth interval is an important indicator of infant health – as research indicates that the recommended length between births for optimal health of mother and child is about 24–36 months (see Rutstein, 2008b). Additionally, because women with more than one child have had a previous pregnancy and delivery there may be an improved understanding of health that comes with the experience of having mothered children in the past. In this model we also see the significance of birth interval ($p < 0.05$) and water source ($p < 0.1$) and that of pre-pregnancy maize price ($p < 0.1$). When the spacing between children is large, LBW is more likely (although this effect is very small in magnitude). In households where water is provided by wells, there is a reduced likelihood of low birth weight as compared to those households with piped water. Again, in terms of maize prices, when prices increase during the pre-pregnancy period, likelihood of LBW decreases.

In Model 2a we include the interaction between mean pregnancy price and NDVI. With the exception of water source, the significant terms observed in Model 2 remain significant. Additionally we again see the significant ($p < 0.01$) positive coefficient for the price and NDVI interaction (as seen in Model 1a) – likely suggesting that when prices are low and NDVI is high babies are most likely to be born at a healthy weight. Average marginal predicted probabilities are very similar to those from Model 1a with only slightly larger differences between the first and third quartiles. Again, when maize prices during pregnancy *and* NDVI are both low then the likelihood of a healthy weight baby decreases.

Discussion

Maize makes up a large portion of the Kenyan diet. Many Kenyans rely on maize bought from the market for their daily

[5] These types of models are referred to by several different names – random effects models, regressions with varying intercepts, hierarchical models, etc. (see Gelman and Hill (2006) for an in-depth discussion of these methods).

[6] The interaction between pre-pregnancy price and NDVI was evaluated as well but was not significant in our analyses.

Table 2
Descriptive results by Livelihood Zone.

Livelihood zone	%LBW	Count	%Urban	%Secondary (or higher)	Avg. birth interval (months)	Max. NDVI (over observation period)	Min. NDVI (over observation period)	Mean pre-pregnancy price (standardized)	Mean pregnancy price (standardized)
Northern Pastoral/ Marsabit Farming	9	33	33	6	47.48	0.697	0.197	0.165	0.157
Northeastern Pastoral/ Mandera Riverine	11	55	62	5	33.78	0.780	0.171	0.257	0.289
Coastal medium potential farming	5	177	67	29	44.21	0.818	0.234	0.254	0.031
Southeastern marginal mixed	8	96	6	27	48.21	0.782	0.444	−0.219	−0.087
Central highlands – high potential	7	888	49	48	54.37	0.827	0.157	−0.208	−0.226
Western high potential	5	419	31	52	44.18	0.830	0.145	0.294	0.164
Lake victoria fishing/ lakeshore marginal	4	232	44	37	41.14	0.760	0.080	−0.037	−0.016

Note: Data are rounded up.

nutrition. However, changes in the supply of maize due to climate (in the form of droughts or reduced rainfall) or other factors, can cause high variability in the prices of this staple product. Food security policy programs and international aid organizations pay close attention to the local prices of staples, with the assumption that when food prices increase then some households will be unable to access food and may experience significant negative health outcomes as a result.

The use of multilevel models facilitate an appropriate analysis strategy grouping births according to the dominant local market. The results of the models highlight the significance of some individual, maternal and household factors in examining LBW outcomes – specifically if the child is one of multiples, mother's height, water source and the interval of time between the current and preceding births. While, the child and maternal factors are consistent with related research, the lack of significant impact of household factors, with the exception of water source, is notable. Piped water appears as a component of increased likelihood of low birth weight in some of the models. Water source is a measure of proximity to urban areas as well as a measure of household wealth[7], in this case we interpret the significance of water source as being primarily related to household proximity to an urban area – these households are likely urban or peri-urban. Our results suggest that these non-rural households are more likely to have LBW babies. This effect could reflect sampling – more urban women are likely to give birth in a hospital or clinic, or it could reflect the vulnerability of non-rural dwellers to food price increases. Further research on the link between water source and urban living – using different metrics of urban access (beyond simply an urban/rural dichotomy) could provide greater insight into this relationship.

On their own, price increases of maize during pregnancy do not appear to lead to nutritional deficiencies in women, at least not those influencing birth weight. In fact, pre-pregnancy food price increases are related to a decreased likelihood of LBW. One explanation for the significance of the negative coefficient of pre-pregnancy price is the possibility that fecundity, in terms of conceptions and carrying pregnancies to term, can be reduced because of food price increases. In other words, the women who are the most sensitive to price increases actually do not end up delivering babies because they are unable to conceive or carry a pregnancy to term. The reasons for the reduced fecundity can be behavioral (related to temporary periods of increased stress, reduced coital frequency or possibly spousal separation) or biological (possibility of increased miscarriage or reduced ovulation) (Bongaarts, 1980; Menken et al., 1981; Torche 2011). In qualitative research in West Africa, impoverished, food insecure women reported experiencing miscarriages during periods when food prices are highest and they increased their wage earning employment (which is normally physically intensive) while decreasing their caloric intake (Grace, Lerner, Sangli, in progress). We may be seeing a similar pattern here but resulting in fewer conceptions among the poorest and potentially most stressed women – those most likely to deliver low birth weight babies had they been able to conceive and maintain their pregnancies.

The significance of the interaction between NDVI and food prices suggests that it is important to account for potential variations in small-scale production, as measured by NDVI, to fully understand the (potentially counter-intuitive) impact of prices.

In terms of production, when very small-scale measures of food production (the NDVI value reflect the vegetation in the 10 km radius around the community) are considered, a relationship between health and food prices is observed. To facilitate the discussion of the interaction effect we include Table 4, a conceptual table reflecting the different NDVI values and food prices with regard to birth weight outcomes. While there is a possibility for unrealistic outcomes (lower left hand side), when actually looking at the data, this situation of very high price and very low production has little impact on the model coefficients. There are 56 births that occurred in a situation where both price and NDVI were within the top quartile of the observations and when these observations are excluded the model results stay about the same (with the exception of NDVI alone being significantly negative). Instead, the model and the coefficients are more heavily influenced by the higher and mid-level NDVI values. The results support the assertion that as NDVI decreases we will see more negative infant health outcomes. Ultimately, this outcome suggests that attending to NDVI values relevant at the community/household-level is arguably of greater importance than prices – at least when using large regional market prices as an indicator of general pricing patterns.

[7] World Bank 2013 indicators http://data.worldbank.org/indicator/SH.H2O.SAFE.UR.ZS

Table 3
Coefficients and significance levels resulting from multi-level regression models of LBW (LBW = 1).

	Model 1	Model 1a	Model 2	Model 2a
(Intercept)	**−2.3992*****	**−2.5910*****	**−2.5804****	**−2.9032*****
Multiple/twin	**3.1854*****	**3.1483*****	**3.1023*****	**3.0732*****
Birth interval			**0.0116****	**1.1483****
Birth order	−0.0577	−0.0569	0.0942	0.0829
Child's sex	−0.1222	−0.1255	−0.0792	−0.0909
Mother's age	−0.0002	−0.0029	−0.0186	−0.0201
Mother's height	**−0.0019***	**−0.0019***	−0.0009	−0.0011
Education (primary)				
Secondary education	−0.4063	−0.4580	−0.5364	−0.6132
Higher education	−0.2666	−0.2802	0.1754	0.1120
Floor type				
Finished	−0.1845	−0.2218	−0.4250	−0.4558
Rural	−0.2031	−0.2233	−0.3697	−0.4215
Water (piped)				
Well	−0.0971	−0.0769	**−0.6915***	−0.6717
Surface	−0.1485	−0.0706	−0.2237	−0.2592
Other	**−1.2722***	−1.2919	−1.1488	−1.2042
Partner Education (primary)				
Secondary education	−0.1275	−0.1316	−0.3642	−0.3813
Higher education	0.1669	0.1488	0.275	0.2604
Don't know/missing response	0.6706	0.6432	1.3613	1.2907
Pre-pregnancy price	**−0.4662****	**−0.4428****	**−0.4056***	**−0.3788***
Price during pregnancy	−0.1497	−0.0561	−0.2397	−0.1153
NDVI	−0.2034	−0.1755	−0.2047	−0.0853
Price × NDVI		**0.6508****		**1.1483*****
AIC	737	734	530	522
	N = 1672	*N* = 1672	*N* = 1284	*N* = 1284

Notes: Data are rounded up. Models also adjust for birth year and birth month but these coefficient estimates were left out of the tables in the interest of space. The random variable, Livelihood zone, in all cases was estimated to have a very small impact. For each model the random effect estimate is virtually 0 suggesting that there is very little variability in the intercept.
Bold indicates significant at at least the 0.1 level.
* Significance based on a p-value <0.1.
** Indicates significance based on a p-value <0.05.
*** indicates p <0.01.

In summary, we theorize that the NDVI values help to distinguish between those households that are dependent on the market for food versus those households that rely on very local household or community-level production. Implying that price may act as a barrier to food for only those families without access to locally produced food (maize, in this case). Because our nested model approach accounted for variation in livelihood zone, or the general amount of agricultural productivity in a large area, we can interpret that the significance of NDVI is unrelated to the climate trends that shape the broader areas of Kenya. Therefore, regardless of where the household is located, when NDVI increases then nutrition seems to be better – and this is especially the case in the presence of low prices.

Table 4
Interpreting the interaction between maize price and NDVI and the relationship to LBW.

	Price	
	Positive	Negative
NDVI		
Positive	Good own production, high price	Good own production, low price
	Model suggests high chance of LBW	Model suggests low chance of LBW
Negative	Poor own production, high price	Poor own production, low price
	Model suggests low chance of LBW	Model suggests high chance of LBW

Conclusions and limitations

The study of infant birth weight in developing countries faces one major challenge – lack of data. The weight of a baby immediately following birth is not often recorded when infants are born without the assistance of a trained health professional. We assume that the poorest mothers, who might face the greatest risks of undernutrition, are likely to be the mothers who birth without any aid. Additionally, underweight mothers who live with constant hunger may not survive pregnancies, labor/delivery or breastfeeding. These women and their stories are unfortunately excluded from our study. Another limitation that we faced in this study was lack of individual-level information about malaria, HIV/AIDS and other illnesses during pregnancy. Any of these health characteristics would impact the mother's ability to absorb nutrients while pregnant, unrelated to environmental or food access conditions. Because the DHS does not collect these data in sufficient detail to determine infection, treatment strategy and timing of infection we are left without this important information. Livelihood zone captures some of this information at a macro-level, the western zones near Lake Victoria have significantly higher levels of HIV/AIDS, for example.

Nonetheless, our study provides additional insight into the relationship between prices and nutrition and supports the usefulness of additional data (specifically, livelihoods and NDVI) to provide a more complete picture of the actual health outcomes of food insecurity. In many ways, our results reinforce what food security experts already know – food insecurity is complex and reflects a person's ability to access food and the availability of food. Our research suggests that when food prices change – just one of the components related to food insecurity – we may see negative impacts on the very youngest members of a population if there are constraints to production at a very local level. Additionally, our results suggest that increases in the cost of maize do not happen in isolation – people may adjust their selling behavior, purchasing habits or rely on other networks (social networks, international and domestic aid support) to meet their food needs. Further research, particularly qualitative assessments, needs to be conducted to determine the varying coping and response strategies available to pregnant women and their families in Eastern Africa.

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References

Abu-Saad, K., Frasier, D., 2010. Maternal nutrition and birth outcomes. Epidemiol. Rev. 32, 5–25.

Block, S., Kiess, L., Webb, P., Kosen, S., Moench-Pfanner, R., Bloem, M., Timmer, C., 2004. Macro shocks and micro outcomes: child nutrition during Indonesia's crisis. Econom. Human Biol. 2 (1), 21–44.

Bloss, E., Wainaina, F., Bailey, R., 2004. Prevalence and predictors of underweight, stunting, and wasting among children aged 5 and under in Western Kenya. J. Trop. Pediatr. 50 (5), 260–270.

Bongaarts, J., 1980. Does malnutrition affect fecundity? A summary of evidence. Science 208 (4444), 564–569.

Brown, M.E., 2008. Famine Early Warning Systems and Remote Sensing Data. Springer Verlag, Heidelberg.

Brown, M.E., Pinzon, J.E., Prince, S.D., 2008. Using satellite remote sensing data in a spatially explicit price model. Land Econ. 84 (2), 340–357.

Brown, M.E., Tondel, F., Essam, T., Thorne, J.A., Mann, B.F., Leonard, K., Stabler, B., Eilerts, G., 2012. Country and regional staple food price indices for improved identification of food insecurity. Global Environmental Change 22, 784–794.

Byerlee, D., Eicher, C.K. (Eds.), 1997. Africa's Emerging Maize Revolution. Boulder Co., Lynne Rienner.

Caldwell, J.C., 1979. Education as a factor in mortality decline: an examination of Nigerian data. Population Stud. 33, 395–413.

Caldwell, J.C., 1994. How is greater maternal education translated into lower child mortality? Health Trans. Rev. 4, 224–229.

Cetin, I., Berti, C., et al., 2010. Role of micronutrients in the periconceptional period. Hum. Reprod. Update 16 (1), 80–95.

Cracknell, A.P., 2001. The exciting and totally unanticipated success of the AVHRR in applications for which it was never intended. Adv. Space Res. 28, 233–240.

Cucó, G., Arija, V., Iranzo, R., et al., 2006. Association of maternal protein intake before conception and throughout pregnancy with birth weight. Acta Obstet. Gynecol. Scand. 85 (4), 413–421.

de Beurs, K.M., Henebry, G.M., 2004. Land surface phenology, climatic variation, and institutional change: analyzing agricultural land cover change in Kazakhstan. Remote Sens. Environ. 89, 497–509, http://dx.doi.org/410.1016/j.rse.2003.1011.1006.

Darnton-Hill, I., Cogill, B., 2010. Maternal and young child nutrition adversely affected by external shocks such as increasing global food prices. The Journal of Nutrition Supplement: The impact of climate change, the economic crisis, and the increase in food prices on malnutrition, 162S–169S.

Devereux, S., 2001a. Famine in Africa. In: Devereux and Maxwell (Eds.), Food Security in Sub-Saharan Africa. London, ITDG Publishing. pp. 117–147.

Devereux, S., 2001b. Food Security Information Systems. In: Devereux and Maxwell (Eds.), Food Security in Sub-Saharan Africa. London, ITDG Publishing, pp. 201–228.

FAO, 2009. Country Profile: Kenya, Food Security Indicators. Frankenberger et al., 1997. Household livelihood security: a unifying conceptual framework for CARE programs. In: Proceedings of the USAID Workshop on Performance Measurement of Food Security, 11–12 December, 1995. United States Agency for International Development, Arlington, VA.

FAO, 2012. The State of Food Insecurity in the World. United Nations Food and Agriculture Organization, Rome, Italy.

Fensholt, R., Nielsen, T., Stisen, S., 2006. Evaluation of AVHRR PAL and GIMMS 10-day composite NDVI time series products using SPOT-4 vegetation data for the African continent International. J. Remote Sens. 27, 2719–2733.

Freeman, H.A., Ellis, F., Allison, E., 2004. Livelihoods and rural poverty reduction in Kenya. Dev. Policy Rev. 22, 147–171.

Funk, C., Budde, M., 2007. National MODIS NDVI-based production anomaly estimates for Zimbabwe. University of California, Santa Barbara, p. 12.

Funk, C., et al. 2010. A Climate Trend Analysis of Kenya. USGS Open-File Report.

Gelman, A., 2006. Multilevel (hierarchical) modeling: what it can and cannot do. Technometrics 48 (3), 432–435.

Gelman, A., Hill, J., 2006. Data Analysis Using Regression and Multilevel/Hierarchical Models. Cambridge University Press, London.

Grobler-Tanner, C., 2006. Understanding nutrition data and the causes of malnutrition in Kenya: a special report by the Famine Early Warning Systems Network (FEWS NET). US Agency for International Development and Chemonics International, Washington DC.

Hobcraft, J.N., 1993. Women's education, child welfare and child survival: A review of the evidence. Health Trans. Rev. 3, 159–175.

Huete, A., Didan, K., Miura, T., Rodriguez, E.P., Gao, X., Ferreira, L.G., 2002. Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Remote Sens. Environ. 83 (1–2), 195–213.

Jayne, T., et al. 2000. Do farmers really benefit from high food prices? Balancing rural interests in Kenya's maize pricing and marketing policy, Tegemeo Institute/Egerton University Working Paper.

Justice, C.O., Vermote, E., Townshend, J.R.G., Defries, R., Roy, D.P., Hall, D.K., Salomonson, V.V., Privette, J.L., Riggs, G., Strahler, A., Lucht, W., Myneni, R.B., Knyazikhin, Y., Running, S.W., Nemani, R.R., Wan, Z.M., Huete, A.R., van Leeuwen, W., Wolfe, R.E., Giglio, L., Muller, J.P., Lewis, P., Barnsley, M.J., 1998. The Moderate Resolution Imaging Spectroradiometer (MODIS): land remote sensing for global change research. IEEE Trans. Geosci. Remote Sens. 36, 1228–1249.

Karnieli, A., Agam, N., Pinker, R.T., Anderson, M.C., Imhoff, M.L., Gutman, G.G., Panov, N., Goldberg, A., 2010. Use of NDVI and land surface temperature for assessing vegetation health: merits and limitations. J. Clim. 23, 618–633.

Keen, C., Uriu-Hare, J., et al., 2003. The plausibility of micronutrient deficiencies being a significant contributing factor to the occurrence of pregnancy complications. J. Nutr. 133, 1597S–1605S.

Kimenju, S., Tschirley, D., 2008. Agriculture and livelihood diversification in kenyan rural households. Tegemeo Institute/Egerton University Working Paper.

Kramer, M., 1987. Determinants of low birth weight: methodological assessment and meta-analysis. Bull. World Health Organ. 65 (5), 663–737.

Martin-Prével, Y., Delpeuch, F., Traissac, P., Massamba, J.-P., Adoua-Oyila, G., Coudert, K., Trèche, S., 2000. Deterioration in the nutritional status of young children and their mothers in Brazzaville, Congo following the 1994 devaluation of the CFA franc. Bull. World Health Organ. 78 (1), 108–118.

Mason, N.M., Jayne, T.S., Chapoto, A., Donovan, C., 2011. Putting the 2007/2008 global food crisis in longer-term perspective: trends in staple food affordability in urban Zambia and Kenya. Food Policy 36, 350–367.

Menken, J., Trussell, J., Watkins, S., 1981. The nutrition fertility link: an evaluation of the evidence. J. Interdisc. History 11 (3), 425–441.

Moore, V., Davies, M., Willson, K., et al., 2004. Dietary composition of pregnant women is related to size of the baby at birth. J. Nutr. 134 (7), 1820–1826.

Morisette, J.T., Pinzon, J.E., Brown, M.E., Tucker, C.J., Justice, C.O., 2004. Initial validation of NDVI time series from AVHRR, Vegetation and Modis, Proceeding of the 2nd SPOT VEGETATION Users conference. Antwerp, Belgium, pp. 149–154.

Mwabu, G., 2008. The production of child health in Kenya: A structural model of birth weight. J. Afr. Econ. 18 (2), 212–260.

Rao, S., Yajnik, C., Kanade, A., et al., 2001. Intake of micronutrient rich foods in rural Indian mothers is associated with the size of their babies at birth: Pune Maternal Nutrition Study. J. Nutr. 31 (4), 1217–1224.

Rutstein, S.O., 2008a. The DHS wealth index: approaches for rural and urban areas. DHS Working Paper No. 40. Washington, DC: United States Agency for International Development.

Rutstein, S.O., 2008b. Further evidence of the effects of preceding birth intervals on neonatal, infant, and under-five-years mortality and nutritional status in developing countries: evidence from the demographic health surveys. DHS Working Paper No. 41. Washington, DC: United States Agency for International Development.

Seidman, D.S., Ever-Hadani, P., Stevenson, D.K., et al., 1988. Birth order and birth weight reexamined. Obstetr. Gynecol. 72 (158), e62.

Sellers, P.J., 1985. Canopy reflectance, photosynthesis, and transpiration. Int. J. Remote Sens. 6 (8), 1335–1372.

Sen, A., 1981. Poverty and Famines. Clarendon Press, Oxford.

Sen, A., 1990. Food, Economics and Entitlements. In: Dreze, J., Sen, A. (Eds.), The Political Economy of Hunger. Clarendon Press, New York, pp. 10–45.

Sen, A., 1997. Entitlement perspectives on Hunger, in Ending the Inheritance of Hunger. World Food Programme, Rome.

Smith, L., El Obeid, A.E., Jensen, H.H., 2000. The geography and causes of food insecurity in developing countries. Agric. Econ. 22, 199–215.

Stein, Z., Susser, M., 1975. The Dutch Famine, 1944–1945, and the reproductive process. I. Effects or six indices at birth. Pediatr. Res. 9, 70–76.

Swamy, G.K., Edwards, S., Gelfand, A., James, S.A., Miranda, M.L., 2012. Maternal age, birth order, and race: differential effects on birth weight. J. Epidemiol. Community Health 66 (136), e142.

Torche, F., 2011. The effect of maternal stress on birth outcomes: exploiting a natural experiment. Demography 48, 1473–1491.

Townshend, J.R.G., Justice, C.O., 1986. Analysis of the dynamics of african vegetation using the normalized difference vegetation index. Int. J. Remote Sens. 7 (11), 1435–1445.

Tucker, C.J., 1979. Red and photographic infrared linear combinations for monitoring vegetation. Remote Sens. Environ. 8 (2), 127–150.

UNICEF, 1990. Strategy for Improved Nutrition of Children and Women in Developing Countries. A UNICEF Policy Review. New York, UNICEF.
Victora, C., Adair, L., et al., 2008. Maternal and child under nutrition: consequences for adult health and human capital. Lancet 371 (9609), 340–357.
Walker, S., Wachs, T., et al., 2007. Child development: risk factors for adverse outcomes in developing countries. Lancet 369 (9556), 145–157.
Williams, A., Funk, C., 2010. A westward extension of the warm pool intensifies the Walker Circulation, drying Eastern Africa. USGS Open-File Report.
Wu, G., Fuller, W., et al., 2004. Maternal nutrition and fetal development. J. Nutr. 134 (9), 2169–2172.
Young, H., 2001. Nutrition and intervention strategies. In: Devereux and Maxwell (Eds.), Food Security in Sub-Saharan Africa. London, ITDG Publishing, pp. 231–264.