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The Economics of Malnutrition

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Introduction

Hunger and undernourishment remain prominent issues worldwide. At the same time, obesity and nutrition related non-communicable diseases are soaring. In 2020, 1 in every 9 people globally are undernourished, over 2 billion people face micronutrient deficiencies and 1 in 3 people are found to be overweight or obese (Development Initiatives, 2020). These coinciding forms of malnutrition are highly alarming consequences of flawed food consumption patterns. Therefore, this dissertation will shed light on several patterns of malnutrition, how they are dispersed both across countries and within countries, and what influences them.

First, Chapter 1 reviews evidence on the relationship between obesity, income and gender both within and across countries. We find that obesity rates change with income, but in a non-linear way. On average, obesity increases with income for poor countries, has no relationship with income for middle-income countries and decreases with income for rich countries. Within countries, obesity is concentrated among richer groups in low-income countries and evenly distributed in middle-income countries. In high-income countries, the poor are the most obese. The relationship differs for men and women, where women are more obese in low-income countries and much more obese in middle-income countries. The gender obesity gap disappears in high-income economies. The geographic concentration of obesity also changes with income growth: from urban areas in poor countries to rural areas in rich countries. Despite these patterns, total obesity rates continue to increase in all countries, and for the world as a whole.

Second, urbanization is expected to have profound implications on health and nutrition. In sub-Saharan Africa, urbanization rates are booming at an annual average rate of 4%, compared to a world average of 2% (United Nations, 2019). Chapter 2 therefore assesses how child stunting, a widely used indicator of adverse nutritional status and health, evolves across different levels of urbanization in ten East African countries. This chapter uses nighttime light intensity as a continuous measure of urbanization to reveal large differences both between and within urban agglomerations. In all ten countries child stunting improves rapidly at low levels of urbanization. At the highest levels of urbanization two different trends can be discerned. For one group of countries the improvements level off, for the other group they deteriorate. The deterioration is especially notable for children from the two richest wealth quartiles. Investigating probable proximate causes of these patterns, we track how a number of

determinants of child health vary with urbanization. Healthcare access and sanitation are found to improve with urbanization and so likely contribute to the initial improvements in child stunting. Child feeding practices, such as meal frequency, consumption of iron-rich foods and diet diversity, also improve initially but deteriorate at the highest levels of urbanization, possibly explaining why child health outcomes do not continue to improve or even worsen in the most economically active urban areas.

Third, as child feeding practices are found to worsen with urbanization, Chapter 3 aims to disentangle dietary patterns between rural areas, secondary towns and highly urbanized areas in Tanzania. In order to do so, this chapter uses detailed information on exact food consumption during a two-week period. This allows the calculation of the macro- and micronutrient content of these diets with respect to the dietary reference intakes (DRIs). We find a significant difference in dietary composition between rural households, those living in secondary towns and those living in Dar es Salaam. Rural households mostly consume vegetables, cereals, roots and tubers, and fruit, but face under consumption issues and consequent nutrient deficiencies. Households living in secondary towns are more likely to fulfill the DRIs for all nutrients, whereas households in Dar es Salaam consume more fat, saturated fat and sugar, but less protein, fiber and key vitamins and minerals. The disparities in nutrient consumption between rural areas and secondary towns are partly explained by differences in wealth, educational levels, food prices and food accessibility. Other factors such as time constraints, supermarket availability and varying consumer preferences may influence the change in diets in Dar es Salaam.

Fourth, food prices highly affect household consumption decisions in developing countries, especially as a large proportion of their income goes towards food (Hirvonen et al., 2020). Therefore, understanding food price evolutions and factors influencing these prices is important to inform appropriate food policies. Using price data from 116 markets in Ethiopia, Chapter 4 explains that real prices of all nutritionally-rich food groups increased significantly (between 23 and 74 percent) from 2005 to 2018. This contrasts with staple crops (grains, roots and tubers), whose price increased only slightly (6 percent), and with oils, fats and sugar, the prices of which decreased substantially (41 to 49 percent). Local price changes of nutritious foods are most highly influenced by prices in areas with a comparative advantage in the production of the product, demand factors in urban areas, and cross-country trade. In contrast, government subsidies and price controls have kept sugar and oil prices low. These findings warn against a degradation in dietary quality due to limited financial access to nutritious foods and the decreasing price of unhealthy foods.

Fifth, this nutrition transition in developing countries from a diet rich in grains, root and tubers, and vegetables to one dominated by processed foods high in sugar and fat (Popkin, 2001), has increased interest in moving the measurement and analysis of nutritional choice beyond calories to a more complete understanding of macro- and micronutrient consumption (Finaret & Masters, 2019). To help move the literature on data collection forward, Chapter 5 uses six different survey modules to measure food consumption across Tanzania, three using diaries and three using recall methods. These modules were chosen to reflect the variety of modules currently in use in multi-purpose household surveys collecting food consumption expenditures at a national scale. Using the percentage consumed relative to the dietary reference intake of calories, protein, fats, sugars, fiber and 16 micronutrients, we find that the household diaries and 14-day recall systematically underestimate nutrient consumption compared to the benchmark personal diaries. The 7-day recall performs better, on average. We also calculate minimum cost diets and cost-of-basic needs food poverty lines in each region, the prevalence and depth of food poverty according to these lines, and the cost of targeted transfers designed to eliminate food poverty. The 7-day recall provides reasonable results whereas the 14-day recall grossly overestimates food poverty and therefore the hypothetical monetary transfer needed to alleviate this poverty.

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Chapter 1. Obesity, income and gender: The changing global relationship*

1.1 Introduction

Obesity is considered one of the major health concerns of the 21st century. As obesity is not only associated with higher mortality (Waxman & World, 2004), but also decreases quality of life and heightens the risk of type II diabetes, cardiovascular disease, hypertension, gallbladder disease, and various cancers (James et al., 2004), it is important to recognize global obesity variations in the context of health and food policies and economic development. Worldwide, the amount of people categorized as overweight now surpasses those categorized as underweight (Mendez et al., 2005; Popkin, 2007). Obesity furthermore presents large external costs to society (Curtis & McCluskey, 2004; Parks et al., 2012), accounting for about 2-6% of total health care costs (WHO, 2007). Identifying best practices in the fight against alarming obesity rates remains challenging due to large cross-country differences (Flynn et al., 2006; Dombrowski et al., 2010). The search for effective policies that prevent long-term obesity-related health problems therefore requires a good understanding of which groups are most vulnerable to obesity.

Obesity is frequently associated with economic development and income growth. For example, it is often emphasized that recent growth in developing countries has led to a rapid increase in obesity (Misra & Khurana, 2008). However, the association between obesity and income is more complex than often argued.

Studies have documented seemingly contradictory observations on the relationship between obesity and income. Several studies show that obesity levels tend to increase when poor countries become richer, suggesting that the relationship between income and obesity is positive (Popkin, 1998; Wells et al., 2012; Malik et al., 2013). However, other studies show that obesity is highest among the least well-off groups in high-income countries, suggesting that the relationship is negative (Giskes et al., 2008; Sallis & Glanz, 2009). In this paper,

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we will explain how and why both relationships can occur by documenting patterns and reviewing evidence on internal (within countries) and external (across countries) relationships between obesity and income and how they change with economic growth and development.

We identify important gender differences in the relationship between obesity and income. Various studies have documented that obesity prevalence is higher for women than for men in specific countries (Swinburn et al., 2011; Roemling & Qaim, 2012; Popkin & Reardon, 2018). As we will show, these gender differences are especially important in middle-income countries, and much less so in the poorest and richest countries. Gender distinctions are important as obesity-related illnesses, such as hypertension and diabetes, are especially harmful to female health, and because maternal physiology influences that of their children, prepositioning them to a higher risk of obesity themselves (Ordovas, 2007; Armitage et al., 2008).

Finally, we also analyze rural-urban differences in obesity and how these relate to income. We show that the geographic concentration of obesity also changes with income growth, from urban areas in poor countries to rural areas in rich countries.

1.2 Across-country observations

1.2.1. Low- and middle-income countries

A large literature documents that obesity increases with economic development, measured by gross domestic product (GDP per capita), for low- and middle-income countries (Ezzati et al., 2005; Lobstein & Leach, 2007; Egger et al., 2012). This relationship is illustrated in Figure 1, which displays the evolution of obesity prevalence with GDP per capita using data from the World Health Organization (2016) and the World Bank (2016).[1] The line in Figure 1 represents the estimated average level of obesity for each level of income. Table 1 summarizes the quantitative results from statistical model estimations of the relationship between obesity and income (and their statistical significance), for the world as a whole and for different categories of income and gender.

Figure 1 and Table 1 document that obesity rates increase with income in poor countries. There are several reasons for this. As the poor grow richer they can afford more food. Moreover, as income increases people not only eat more but their diet portfolio changes, and not necessarily to a healthier basket (Drewnowski & Popkin, 1997). As income rises, diets shift from traditional

[1] Economists typically use the logarithm of GDP rather than GDP in illustrations – as has been used on the x-axis of Figure 1.

home-cooked meals to ready-made processed food and a more "westernized" diet. Income growth is also associated with a change in lifestyle and occupation. The poor often work in labor-intensive manual jobs that require high levels of energy expenditure, while higher income economies are associated with a more sedentary lifestyle involving less energy-intensive jobs.

Culture and social preferences may also play a role. Studies show that in developing countries, a larger body mass is sometimes preferred as it is associated with power, beauty, health and affluence (Fernald, 2009). Brewis et al. (1998) found this in the Polynesian Islands. Kruger et al. (2005) furthermore found that in African countries thinness was often associated with HIV/AIDS and other diseases, resulting in positive attitudes towards a larger body size. Rguibi & Belahsen (2006) also found that an image of an overweight person was seen to be healthier than the skinnier options in a study in Morocco.

Another factor is that access to healthcare, education, wholesome food and recreational activities promoting weight management remain relatively scarce in low- and middle-income countries (Malik et al., 2013). Finally, urbanization rates, which are correlated with income growth, may also play a role as a larger percentage of the population is confronted with more energy-intensive diets, higher in processed foods, sugar and oils, typical of urban regions (Popkin 2006). The combination of these factors makes that obesity rises with income (Popkin et al., 2012).

1.2.2. Middle- and high-income countries

However, the positive relationship between obesity and income changes at higher levels of income. There is no longer a significant relationship between income and obesity once a certain income level has been reached (Ezzati et al., 2005; Dinsa et al., 2012; Egger et al., 2012). Figure 1 illustrates that for the range of middle-income countries, which includes countries such as Russia, Turkey and Brazil, there is no significant (positive or negative) relationship between income and obesity.

The data and other studies also suggest that as incomes increase even further that the relationship between income and obesity may change from positive to negative, and that average obesity is lower again at the highest income levels (e.g. Groth et al., 2009). Rokholm et al. (2010) find that childhood obesity is decreasing in countries such as Sweden, Switzerland, France and Australia.

The regression results in Table 1 support these conclusions. There is a significant non-linear relationship between income and obesity, reflected in the significant estimates of the quadratic term of the regression (for "all countries" in column (1)). This changing relationship is also consistent with the statistical

analyses for the three different income groups (columns (2) to (4) in Table 1). The coefficient of GDP per capita shifts from significantly positive in low-income countries (column (2)) to not significant in middle income countries (column (3)) to negative in high income countries (column (4)). The negative effect in high-income countries is not significant for the population as a whole but it is for women. This suggests significant gender differences, which we will discuss in Section 1.5.

One can calculate the maximum of the obesity-income relationship using the quadratic regression results and thus identify the "turning point". The declining trend in obesity at higher income levels starts at an income level of about 43,000 US dollar (US$)[2], approximately the income level of Finland today.

The literature has forwarded some reasons for the changing relationship between income and obesity at higher income levels. One factor is the adverse reaction to obesity and the social stigma of being overweight in high-income countries (Prentice, 2005). As explained above, this is different from cultural and social preferences in low- and middle-income countries, where a larger body mass is desirable. Popkin (2014) argues that the effect of cultural differences for body size preferences are reinforced by the supply, availability, and affordability of specific types of food. For example, food shops and supermarkets in low- and middle-income countries offer mostly processed and ready-made meals, while supermarkets in rich countries increasingly offer a wide variety of fresh fruits and vegetables, low calorie foods, "superfoods", etc. This is not only due to differences in preferences but also due to the fact that people in high-income countries, on average, have more resources to spend on healthy diets, including fresh fruit and vegetables, high-quality meat and fish. In addition, access to healthcare, education and recreational activities promoting weight management are more available in high-income countries (Malik et al., 2013). So, also here, it is a combination of factors that cause a different relationship between obesity and income than in lower income countries.

1.3 Within country observations

Studies also document a changing relationship between income and obesity *within* countries – and these changes are consistent with the changing relationship documented *across* countries. In low-income countries obesity prevalence is found to be highest among the upper-class (Mendez et al., 2004; Jones-Smith et al., 2012). This phenomenon has been highlighted as part of the double bur-

[2] This is calculated from the quadratic equation for total obesity levels in Table 1.

den of malnutrition, with large portions of the population suffering from under-consumption and micronutrient deficiencies, while overweight and obesity are also (and increasingly) a problem (Swinburn et al., 2011). Figure 2 illustrates how in countries such as Benin and Ghana, with a GDP per capita around 1,000US$ to 1,500 US$, obesity is more prevalent in higher income groups[3]. While obesity rates in Benin are still relatively low at every level of income, obesity in Ghana reaches about 45% for the highest income groups. In Benin and Ghana, the poorest 20% of the population only make up about 2-7% of the total number of obese people (Table 2).

Figure 2 and Table 2 also illustrate how the distribution of obesity shifts from being concentrated among richer people in low-income countries to being relatively equally distributed in middle-income countries. In middle-income countries like the Dominican Republic and Turkey, with a GDP per capita between 7,000 US$ and 11,000 US$, obesity prevalence is relatively similar at all income levels. In middle-income countries poverty and obesity are similarly distributed. In the Dominican Republic and Turkey about 15-21% of obese people belong to the poorest 20% of the country (see Table 2). Income differences are thus not a major factor influencing obesity levels in these countries.

The shift from obesity being a problem for richer people in low-income economies to (also) being a problem for poorer people continues at higher incomes (Martorell et al., 2000; Monteiro et al., 2004). Griffith et al. (2016) document that in high-income countries, like the UK, obesity is most prevalent among the poorest. Figure 2 illustrates that in high-income countries such as Spain and Germany, with a GDP per capita of 30,000 US$ and above, obesity prevalence is lowest in high-income groups and highest among the poorest in society. In Spain and Germany, the poorest 20% make up 26-27% of the total number of obese people (Table 2).

In high-income countries the brunt of the obesity burden thus falls on the poorest in society. It is the richer people in high-income countries that are more health aware, can allocate more time and resources to healthy diets and exercise regimes, while the poor consume more fat, sugar and energy-dense food, as diets high in lean meat, fish, vegetables and fruit are too expensive (Drewnowski & Darmon, 2005; Headey & Alderman, 2019) or scarcely available (Wrigley, 2002; Walker et al., 2010). Here it appears that both supply and demand factors play a role. On the supply side, recent studies have associated the relatively high price and low availability (and high opportunity costs) of healthy foods for the poor with so-called "food deserts", i.e. the absence of

[3] In Figure 2, data on female obesity is used as data for total and male obesity rates is not available for most low- and middle-income countries.

fresh and healthy produce in supermarkets, or the absence of supermarkets altogether, in low socioeconomic areas in countries such as the US (Walker et al., 2010) and the UK (Cummins & Macintyre, 2002).

1.4 Evolution over time

1.4.1. Obesity and income growth patterns

The non-linear relationship between income and obesity may suggest that if countries and people become richer over time that their obesity rates will stop growing and may eventually decline again. However, if we look at changes in obesity over time, there is the striking observation that obesity levels have never decreased in any country so far. Hence, the observed negative correlations between income and obesity at the higher income levels should not be interpreted as that obesity *levels* will decline when incomes grow, but rather that obesity *growth* with income is slower in rich countries than in middle-income countries.

This conclusion is illustrated in Figure 3, which shows how obesity and incomes have evolved over the 50 year period between 1976 and 2016. Since it was not possible to include all countries, Figure 3 illustrates these historical changes for the six countries included in Figure 2. The first key observation is that obesity has increased everywhere – i.e. in all countries and in all time periods (see Figure 3A). This is not only the case for the six countries in Figure 3, it is the case for all countries in the WHO dataset.

A second observation is that during the latest decade in the data (from 2006 to 2016) the curves become steeper for the richest countries. Although part of this is caused by the log-scale on the horizontal axis, it does suggest that there has been a significant increase in obesity in the middle- and high-income countries despite limited growth. In fact, in the case of Spain, obesity has increased by 5 percentage points (from 22% in 2006 to 27% in 2016) despite a decline in incomes caused by the economic crisis of 2009.

The third key observation is that the obesity growth rates differ significantly between income groups. They are lowest for poor countries and highest for middle-income countries (see Figure 3B). Obesity has grown by about 22 percentage points in the Dominican Republic and by 24 in Turkey, much higher than in the poorest countries (7 in Benin and 8 in Ghana), but also significantly higher than in the richest countries (around 16 for Spain and Germany).

These differential growth rates are not just the case for these six countries. The growth patterns in Figure 3 are consistent with average growth patterns across all countries. Figure 4 illustrates how, over the period 1976-2016, the average growth of obesity prevalence was lowest in low-income countries with 7.4 percentage points. Middle-income countries experience the strongest

growth in obesity with 17.0 percentage points. For high-income countries, obesity growth was a bit less, but still high (15.8 percentage points).[4]

The result of this continued growth of average obesity levels over time, and the differential growth rates of obesity between income groups, is that the relationship between obesity and income is also changing over time. Figure 5 illustrates how the estimated relationship of average obesity with income is moving upwards over time, in particular in the middle- and high-income regions. Hence, while the difference between obesity levels is getting smaller at middle and higher income levels (as we documented in Sections 1.2 and 1.3), the overall obesity level is simultaneously increasing.

Moreover, the historical changes are large. At an average income of 10,000US$ per capita – an income level close to that of Turkey and Argentina today (and which corresponds to a level of 4 on the horizontal log GDP per capita axis in Figures 1 and 5) – the average obesity level was 10% in 1976, 16% in 1996 and 23% in 2016. This can also be seen from Figure 3A: the income level of Turkey in 2016 was approximately that of Spain in 1990 and of Germany in 1980. However, the obesity levels for Turkey in 2016 (33%) are much higher than those for Spain in 1990 (17%) and for Germany in 1980 (12%).

The more rapid growth in obesity levels for middle-income countries compared to high-income countries can be, at least partially, attributed to biological factors (Prentice et al., 2005). An extensive literature, commencing with the Barker (1994) hypothesis, states that fetal undernutrition is an important contributor to obesity. Fetal malnutrition triggers a host of hormonal, anatomical and physiological changes that improve child survival in a food insecure environment (Gluckman & Hanson, 2006). However, if paired with a resource-rich postnatal environment, these genetic alterations may contribute to a more accelerated weight gain. These theories are supported by studies analyzing the long-term effect of maternal famine exposure on children born afterwards (Ravelli et al., 1999; Clarkin, 2008). Adults living in middle-income countries, are more likely to have suffered from malnutrition during their fetal development, compared to adults living in high-income countries. The chance that these adults become obese later on in life is therefore greater when experiencing income growth.

A similar biological effect comes from food insecurity in early childhood. Infant stunting leads to an impaired fat metabolism (Hoffman et al., 2000) and

[4] Studies analyzing within-country differences, following children from a variety of households with differing socioeconomic statuses, yield similar conclusions. Children from poor households are more likely to face issues of overweight or obesity in adulthood (Poulton et al., 2002; Power et al., 2005).

a relatively higher gain in fat mass compared to lean body mass (Martins et al., 2004). Until quite recently, middle-income countries still had a high prevalence of stunting, a typical indicator of food insecurity. The average stunting rate in middle-income countries was 43.8% in 1990 (Table 3). These rates have improved significantly over the past two decades (to 23.0% in 2016). However, it implies that many more adults in middle-income countries (who were born before 1990) have experienced stunting, affecting their fat metabolism and stimulating obesity, compared to high-income countries (where stunting was on average less than 5% in 1990).

A related explanation for the differences in obesity levels between middle-income and high-income countries is through psychological channels. After periods of deprivation, an increased excitement over the ability to buy more foods accompanied changing food preferences. Russell et al. (2016) find that children from the most deprived income quintile are more likely to consume "feel good" foods and less likely to consume fruit and vegetables in adulthood. Higher childhood exposures to stress are associated with rapid weight gain during adolescence (Koch et al., 2008). Middle-income country adults are more likely to have experienced periods of hunger or nutritional deprivations, increasing current and future obesity rates as parental eating behaviors influence the development of their children's eating behaviors (Savage et al., 2007).

These biological and psychological factors are reinforced by fast structural changes in food distribution systems in middle-income countries, often referred to as the "supermarket revolution" (Reardon & Berdegue, 2002), rapid urbanization (Smil, 2001) and the decline in food prices (Schmidhuber & Shetty, 2005). In combination with social and cultural differences in high-income countries leading to behavioral changes (discussed above) these factors cause a stronger growth in obesity in middle-income countries than in high-income countries.

1.4.2. Economic development and global obesity

The country obesity-income relationships and growth patterns discussed so far are based on unweighted country averages. This means that large countries have the same impact on the relationship as small countries. This is an appropriate approach as large and small countries are equally valid as data points in this analysis. However, if we want to obtain an idea about the relationship between obesity and income from a global health perspective, it is also useful to look at the relationship taking into account the number of (obese) people living in each of these countries. From this we can determine how large of an issue rising obesity rates are in absolute numbers of people.

In Figure 1, the two most populated countries in the world, India and China, are far below the estimated (average) relationship. This suggests that taking the number of people into account may yield a different relationship or growth pattern. Figure 6 therefore illustrates the world growth pattern of obesity and income with population-weighted and unweighted country data. The difference is substantial. The average global obesity level in 2016 is 19% with unweighted data and 10.5% with population-weighted data. Much of this is due to the fact that some of the largest countries, especially China and India, have lower levels of obesity than the average for their income category, and thus pull down the average when their size is taken into account[5]. The weighted income levels are substantially higher than the unweighted, moving the curve to the right.

That said, some key conclusions are the same for both patterns. There has been significant growth in obesity over the past 50 years and this is correlated with significant income growth. During the latest decade in the data (from 2006 to 2016) the curves clearly change, becoming almost vertical. Despite relatively limited income growth, there has been a very significant increase in obesity globally (around 3 to 4 percentage points depending on the indicator).

1.5 Gender differences

1.5.1. Across countries

In many countries there are important differences between male and female obesity rates. Globally, the prevalence of obesity is around 50% greater for women than for men (Wells et al., 2012). However, this gender gap is not the same for all countries (Garawi et al., 2014).

Interestingly, these gender differences are also correlated with income. More specifically, the gender obesity gap is much higher for middle-income countries than it is for low-income countries or high-income countries. Panel A of Figure 7 illustrates the estimated relationship between average obesity levels and income for males and females – similar to Figure 1 but now disaggregated by gender. Panel B of Figure 7 presents the gender obesity gap, which represents the difference between the two graphs in panel A, and how it evolves with income.

[5] Some studies have cautioned against a common measure of obesity across cultures and regions (Hoang & Wong, 2007; Wen et al., 2009). They argue that South- and East-Asians face greater adverse metabolic effects of a BMI over 30 (the standard global definition of obesity) compared to Caucasians. They suggest to define obesity by a BMI greater than 25 in South- and East-Asian regions. This would bring the two lines in Figure 6 closer together.

The female obesity relationship with GDP per capita follows a clear non-linear trajectory - increasing until a certain income level and declining afterwards. The positive relationship in low-income countries and the negative relationship in high-income countries are both statistically significant (see Table 1). There is no significant relationship between income and female obesity for middle-income countries.

For males, the relationship between obesity and income is somewhat different. Obesity increases at all income levels, and although the curve levels off, there is no turning point in the regions (countries) included in the WHO database.

For most countries, female obesity is higher than male obesity. In the poorest countries, average obesity is already higher for women. At higher levels of income, the gender obesity gap widens further, with the average number of obese women growing more rapidly than men. The gender obesity gap peaks for middle-income countries. Note that there is still large variation in the observations. For example, in several middle-income countries in Eastern Europe (such as Bulgaria, Hungary, Romania and Slovakia) and in some African countries (such as Nigeria), men are more obese than women. At the peak, the gender obesity gap is almost 10 percentage points (see Figure 7B), with the average obesity prevalence for women around 24% and for men close to 15% (see Figure 7A). In other words, on average, women are 60% more likely to be obese than men at these income levels.

Beyond this peak, the gap closes as female obesity first slows down and then starts declining, while that of men keeps rising, albeit slower. For women, the change from a positive to a negative relationship between obesity and income is at an income level of about 38,000[6] US$, significantly below the estimated turning point for the total population (around 43,000 US$). For male obesity, there is no turning point in the estimated global relationship presented in Figure 7, only a slowing down of the increasing obesity rates.

The result of these diverging trends is that at high-income levels there is no longer a significant gender difference in average obesity prevalence. The trend line suggests that the obesity gap may even reverse at high levels of income, with males becoming the more obese gender. This is already the case in Japan, in all Scandinavian countries, and in Northern European countries like Belgium, France, Switzerland and Germany.

[6] Calculated from the quadratic regression of female obesity in Table 1.

1.5.2. Over time

The conclusion from the cross-country data analysis is consistent with the analysis of historical data and how obesity has grown for men and women over the 50 year period between 1976 and 2016, as illustrated in Figure 8. Panel A of Figure 8 illustrates these historical changes for three of the six countries included in Figure 2 and 3. Panel B illustrates the historical evolution for several large countries.

The key findings are consistent across the graphs. In low-income countries, such as Benin (panel A) and India (panel B), male and female obesity rates start off at similar levels in 1976, but over time, the obesity rates start to diverge, with female obesity growing faster. In middle-income countries, such as Turkey (panel A) and Russia (panel B), there is a large gap with female obesity rates roughly twice as high as those for males. In high-income countries, such as Germany (panel A), and France and the USA (panel B), male and female obesity rates converge again. In 1976, women had higher rates of obesity in all three countries but by 2016, male and female obesity prevalence is almost the same, with males already having higher obesity rates in Germany.

An important point to emphasize is that the "gender convergence" in obesity at high income levels is not due to the fact that female levels of obesity are actually declining, but because obesity among women is growing slower than for men. Figure 8 shows, just as Figure 3, that obesity levels have not decreased so far, neither for men nor for women. Hence, the convergence of gender obesity levels at higher income levels is not because female obesity *levels* have declined when incomes grow, but rather that obesity *growth* with income is slower for women than for men at high income levels.

The illustrated patterns in Figure 8 are consistent with the average changes for all countries. Figure 9 displays the average growth rates for obesity in low-, middle- and high-income countries between 1976 and 2016 for men and women. In low-income countries, obesity growth is stronger for women (9.8 percentage points) than for men (4.8). In middle-income countries, female obesity still grew more (18.3) than male obesity (15.5). However, in high-income countries the growth in obesity prevalence for women declined to 14.4, while it continued to increase for men (17.7 percentage points).

1.5.3. Within-country observations

The data suggest that for males the obesity-income relationship may also eventually turn around at (very) high income levels. Firstly, our statistical analyses show that while there is a strong positive relationship between average male

obesity and country incomes at low levels of income, this is no longer significant for middle-income countries, and even less at high levels of income (Table 1).

Secondly, although within-country obesity distribution data for men are only available in high-income countries, the available data do suggest that there is also a negative relationship between obesity and income in high-income countries for men, as there is for women. Available data are presented in Figure 10 for Germany and Spain. The illustrated relationship is negative, but less strong than that for women (see Figure 2) – consistent with the across-country differences.

1.5.4. Explanations for the gender obesity gap

There are several explanations for these (changes in) gender differences in obesity and income. Studies show that, at the lowest levels of GDP, females often have less access to nutritious food because they are less income secure and have lower wages than men (Wells et al., 2012). Garawi et al. (2014) furthermore argue that discriminatory social practices that are rooted in the economic, political and social structures of developing societies may lead to higher female obesity. Improving women's status may therefore be key in addressing the global obesity epidemic in the long-run, not only benefitting women themselves but also their offspring (Wells et al., 2012).

Cultural aspects may also play a role. As explained in Section 1.2, studies conclude that in various low- and middle-income countries a larger body size is preferred, as it is seen as a desired status signal and a sign of health and prosperity (Holdsworth, 2004; Fernald, 2009). This seems to be particularly the case for women as it is also seen as a sign of higher fertility (Kanter & Caballero, 2012).

The growth of the gender obesity gap in middle-income countries seems to be caused by several factors. On the one hand, middle-income countries continue to experience similar issues of female inequality and status as low-income countries. The transition away from agrarian jobs has also decreased the physical activity of women more than for men (Ismail et al., 2002; Snodgrass et al., 2006). In addition, women now also face a growing opportunity cost of time. Here the growing market for time-saving, pre-packaged foods have contributed further to already alarming obesity levels (Popkin, 2006), especially in urban centers (more on this in Section 1.6). This may have especially large effects on women as they are over-motivated to ensure food security in later life after having experienced periods of deprivation during childhood (Olson et al., 2007). Hence, the combination of these factors is likely causing a growing gap in obesity levels between men and women in middle-income countries.

In rich countries, several studies document gender differences in healthy behavior and diets with women being more likely to focus on healthy eating and activities (Zunft et al., 1997; Furnham & Kirkcaldy, 1997; Fagerli & Wandel, 1999; Wardle et al., 2004). Although women have a higher preference for dairy-based comfort foods (Wansink et al., 2003), men in both the United States and Europe show a higher intake of other food and drinks contributing to obesity, such as alcoholic beverages (Kant et al., 2007; Castetbon et al., 2009). Cultural factors and social network effects may reinforce this (Courtenay, 2000; Christakis & Fowler, 2007).

Analyzing these gender differences and their causes is important not only for people themselves but also for future generations. As female obesity predispositions future generational weight issues of both males and females through metabolic imprinting, it is imperative to carefully analyze these gender disparities (Sullivan & Grove, 2010; Josefson, 2012).

1.6 The role of urbanization

Economic development and income growth are correlated with urbanization.[7] Many studies have argued that urbanization is a key factor in the globally rising obesity rates (Christensen et al., 2008; Wagner & Brath, 2012, Malik et al., 2013). However, also here the relationship is more complex than often argued.

Initially, urbanization was mostly seen as a positive influence on food security as it was associated with declining undernourishment (Delgado, 2003; Huang & Bouis, 2004). However, from 2000 onwards, studies pointed at urbanization and overconsumption. They argued that urban areas in lower income countries shifted towards more energy intensive diets, dominated by processed 'fast-food' and higher oil and sugar intakes, with a growing dependence on street foods (Popkin, 2006). In some countries, street foods account for almost three-quarters of the total calorie intake of the urban poor and middle-income groups (Maxwell et al., 2000; Kinabo, 2004; Maruapula et al., 2011). Urban diets are therefore lower in essential vitamins, minerals and fibre, and higher in energy, fats and sugars (Kearney, 2010; Ameye, 2017). Combined with a more sedentary lifestyle, this leads to increases in obesity (Popkin et al., 2012).

Interestingly, recent studies provide apparently contradictory evidence showing that it is in fact rural areas driving up global obesity rates (Jaacks et al., 2014). Bixby et al. (2019) find that over 55% of the rise in global BMIs between 1985 and 2017 come from rural areas, with this percentage reaching more than

[7] The correlation between GDP per capita and the percentage of urban population is 60% (WB, 2016).

80% for low- and middle-income countries. These figures indicate a closing and even reversal in the gap between rural and urban obesity rates, which Popkin & Reardon (2018) suggest may be due to the transformation of rural areas to resemble urban areas.

In the rest of this section we analyse the relationship between obesity and urbanization, identifying patterns with our data as in previous sections.

Figure 11 compares obesity rates from rural and urban regions using the most recent DHS and European Health Interview Survey data. Pooling all countries, urban obesity rates are on average 3 percentage points higher than those in rural regions, at about 20% and 17% respectively. However, when dividing our sample into low-, middle- and high-income countries, we find that differences in obesity rates between rural and urban regions change.

In low-income countries, urban areas have much higher levels of obesity: 18% compared to 7% in rural areas. In middle-income countries the difference between rural and urban obesity is smaller, with high obesity rates in both areas, at 29% and 26% respectively. In high-income countries, the pattern reverses. Rural regions have higher levels of obesity at 19% compared to 15% in urban areas.

Figure 12 presents the change in obesity prevalence for rural and urban regions. Data are only available for low- and middle-income countries from 2001 to 2012[8]. For low-income countries, rural obesity levels are lower than urban obesity levels, in all time periods. In middle-income countries, there is a clear convergence in obesity rates. Urban obesity rates were higher from 2001 to 2006, but rural obesity rates caught up from 2006 to 2012. Hence, while there are no historical data on changes over time for high-income countries, what is available shows patterns of convergence between urban and rural areas in middle-income countries.

These rural-urban obesity patterns are also mirrored in the distribution of obesity by income groups within countries. To compare with Figure 2, we separate the rural and urban population in low- and middle-income countries[9] in Figure 13. In the low-income countries (Benin and Ghana) total urban obesity is much higher than rural obesity. However, the increasing relationship between household income and obesity holds in both rural and urban areas in Benin and Ghana. Moreover, the obesity gap between the income categories is much larger than the urban-rural differences within income groups.

The relationship is different in middle-income countries. The total gap is smaller. In Armenia, rural obesity is already higher than urban obesity. Rural

[8] These are rough dates depending on year of data collection.

[9] Data on both within-country wealth categories and rural-urban classifications are not available for high-income countries. Turkey is replaced by Armenia, a middle-income country for which we have data.

obesity rates exceed those of urban areas, at all income levels. In the Dominican Republic, urban obesity is higher overall, but especially in income category 2 and 3. At higher income levels, rural areas have obesity levels equal to or higher than urban areas.

In summary, available data indicate that obesity is higher in urban areas in poor countries, but lower in urban areas in rich countries. Despite incomes being typically higher in cities, they are often associated with unhealthier food options and limited space for physical exercise in low- and middle-income countries (Pirgon & Aslan, 2015). Hunger and macronutrient deficiencies are less common in megacities, but these go paired with large micronutrient deficiencies, indicating a lower quality diet. Households living in urban slums also have limited cooking facilities to provide wholesome meals, therefore relying on unhealthy street food and fast-food for sustenance. These phenomenon reverse in high-income countries, where urban areas are associated with increased availability of organic and health foods, as well as exercise and sports facilities. This transition from urban to rural areas as main location of obesity occurs when countries reach "middle-income" status.

1.7 Summary and conclusions

Obesity changes with income, but in a non-linear way. This relationship also differs for men and women. These conclusions follow from a range of studies and data analyzing both cross-country and within-country differences in obesity prevalence. The complex relationship between obesity, income, urbanization and gender is summarized in Table 4.

Globally, obesity is lowest in the poorest countries and is higher for countries with a higher GDP per capita. At middle-income levels there is no significant correlation between incomes and obesity levels. For high-income economies, the correlation is negative, but only significant for female obesity.

This non-linear relationship is not because obesity declines with income growth in higher income countries, but because average obesity levels have never decreased in any country thus far. The observed negative correlations between income and obesity at the higher income levels are because obesity *growth* with income is slower in rich countries than in middle-income countries.

The change of average obesity with income is also reflected in changes of the obesity distribution within countries. In poor countries, the rich are more obese. In middle-income countries there is little correlation between income and obesity. In rich countries, obesity is concentrated among the poorest groups of the population.

There are significant gender disparities in obesity prevalence worldwide. Females are more obese in low-income and middle-income countries, with the gender gap being highest in middle-income countries. For middle-income countries, this gap also widens over time. In high-income economies, the gender obesity gap disappears as the growth of female obesity is slower than that of male obesity.

Urbanization, which is correlated with income, is also correlated with obesity in a non-linear way. In low-income countries obesity is higher in urban areas than in rural areas. In high-income countries the rural-urban obesity gap is reversed.

A series of studies have tried to identify the causes of these differences and the changing relationship with income. They show that a combination of several factors, including economic, social, cultural, institutional, psychological and biological factors, play a role. Addressing obesity problems therefore requires an approach that targets more than just one factor or cause. Still, there is much to learn. An important area for future research is to better understand which factors explain these differences, to what extent these effects are conditional to specific circumstances and how these insights can be used to design better prevention campaigns and more effective targeting of health policies in this area.

A possible positive insight from our analysis, for the design of policies and campaigns to address obesity across the globe, is the variation in obesity levels among low- and middle-income countries. This variation is very large, meaning that although the average patterns are clear, there are potentially important lessons that can be drawn from countries with similar income levels but relatively low levels of obesity (or gender gaps) in order to reduce the obesity rates in the countries, or groups within the country, with a high obesity prevalence.

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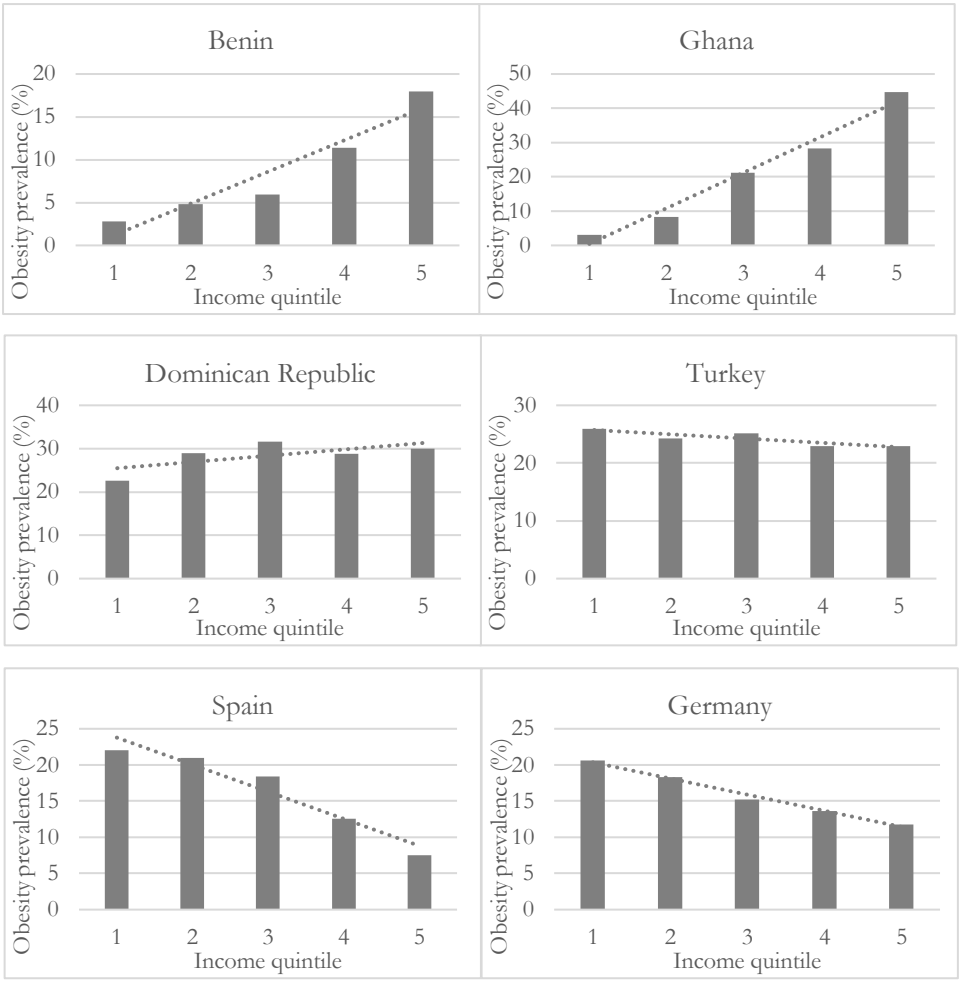
1.9 Figures

Figure 1 | Worldwide obesity prevalence and GDP per capita



Source: WHO (2016) and WB (2016)

Figure 2 | Within-country female obesity prevalence and income*

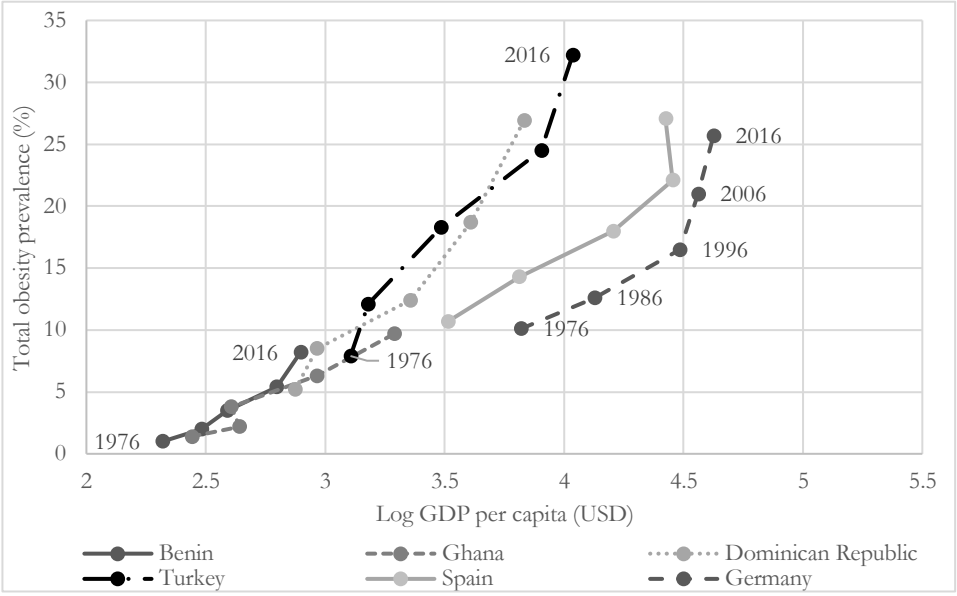


Source: Demographic and Health Surveys (Benin 2011, Ghana 2014, Dominican Republic 2013), European Health Interview Surveys 2014 (Turkey, Spain, Germany)

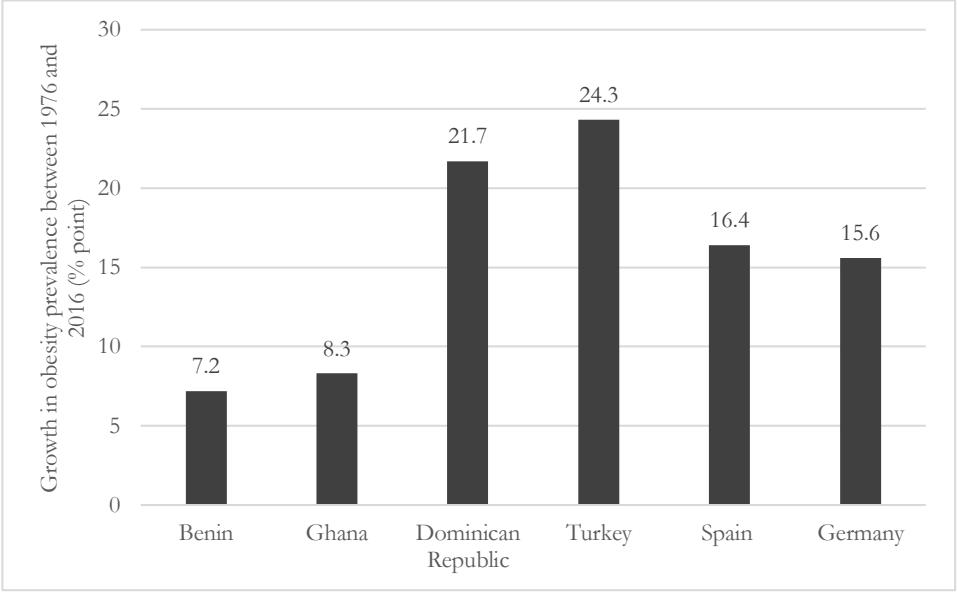
* For low- and middle-income countries, this type of data is only available for females.

Figure 3 | Growth of obesity prevalence and GDP per capita over time (1976-2016)

3A: Obesity and income 1976-2016

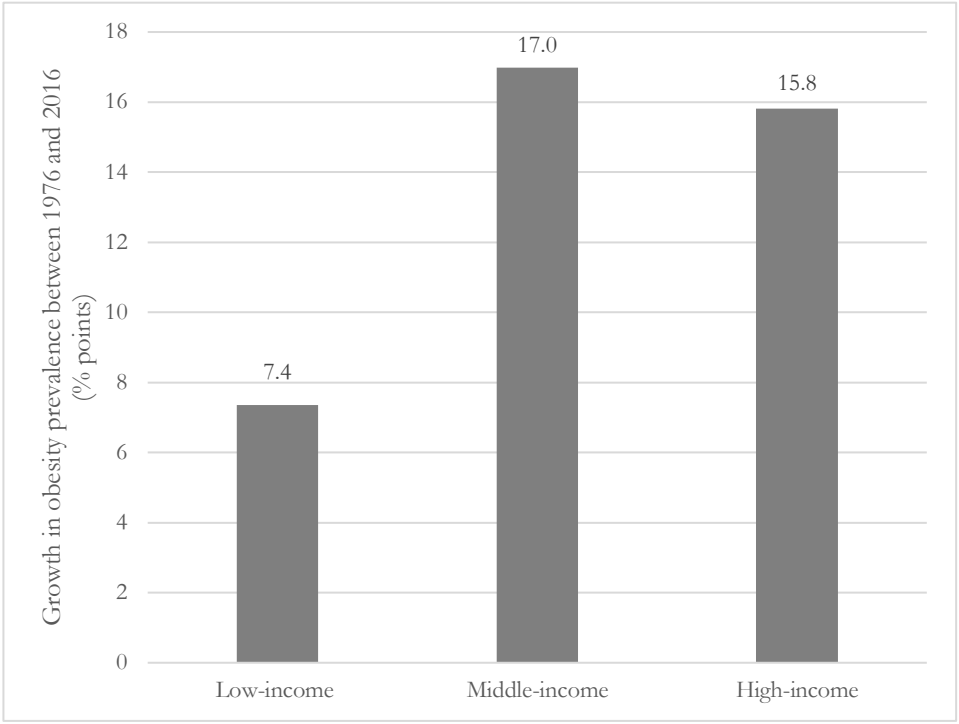


3B: Growth in obesity prevalence (% points) between 1976 and 2016



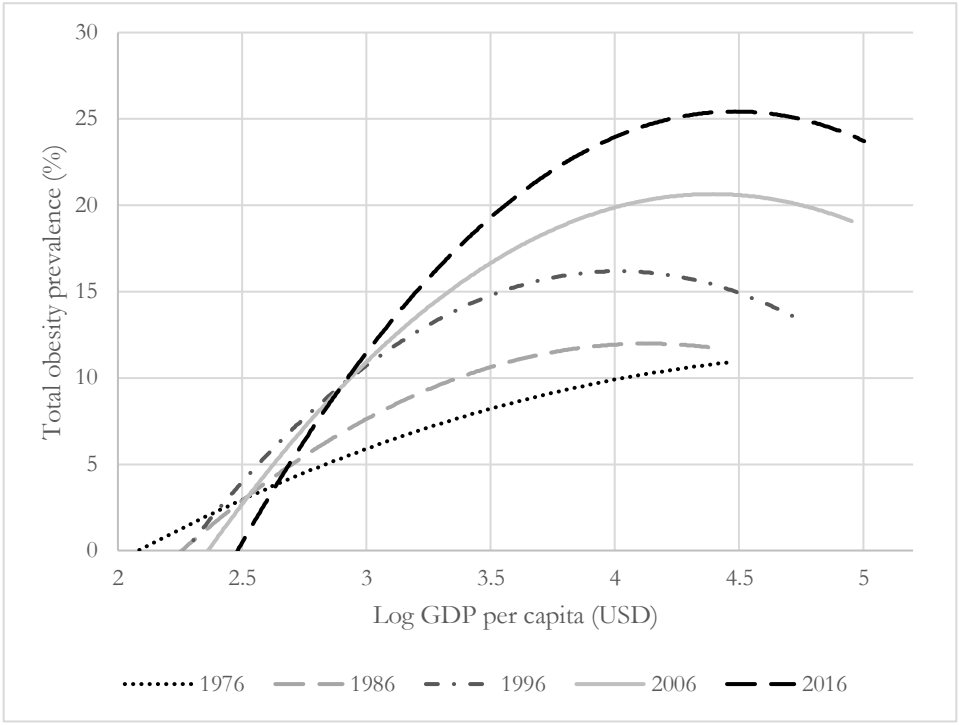
Source: WHO (1976, 1986, 1996, 2006, 2016) and WB (1976, 1986, 1996, 2006, 2016)

Figure 4 | Growth in obesity prevalence (% points) between 1976 and 2016



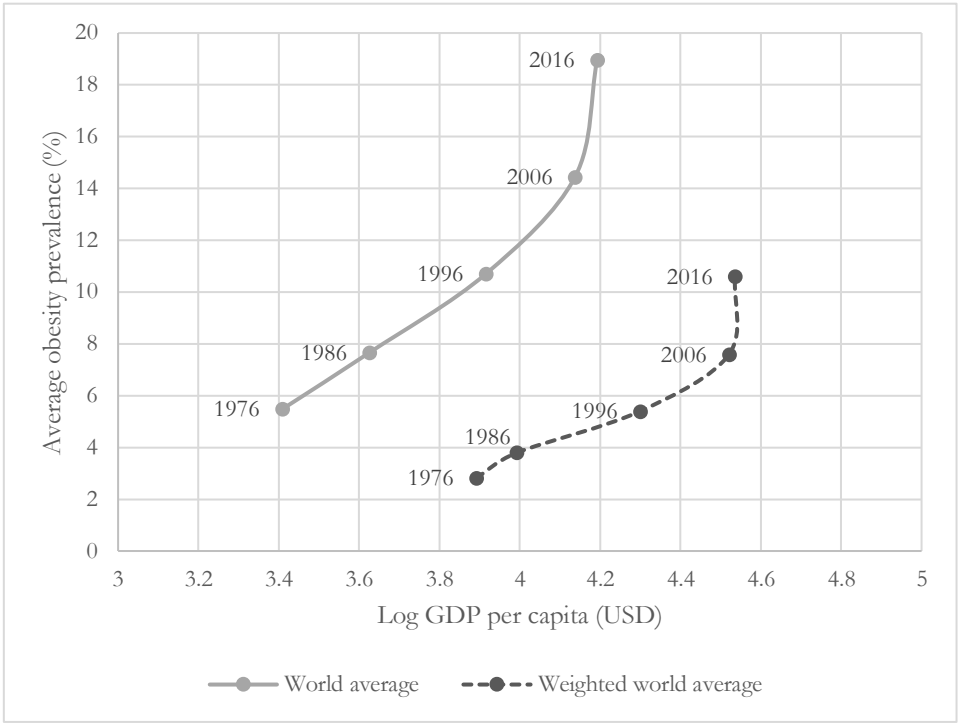
Source: WHO (1976, 1986, 1996, 2006, 2016) and WB (1976, 1986, 1996, 2006, 2016)
Note: Low-income, middle-income and high-income countries are classified by dividing the range of the log GDP per capita by 3. Low-income countries have a log GDP per capita lower than 3.3 (GDP per capita around 2,000 US$), middle-income countries between 3.3 and 4.2 (GDP per capita around 16,000 US$) and high-income countries above 4.2.

Figure 5 | Estimated relationship between countries' obesity prevalence and GDP per capita at different times



Source: WHO (1976, 1986, 1996, 2006, 2016) and WB (1976, 1986, 1996, 2006, 2016)

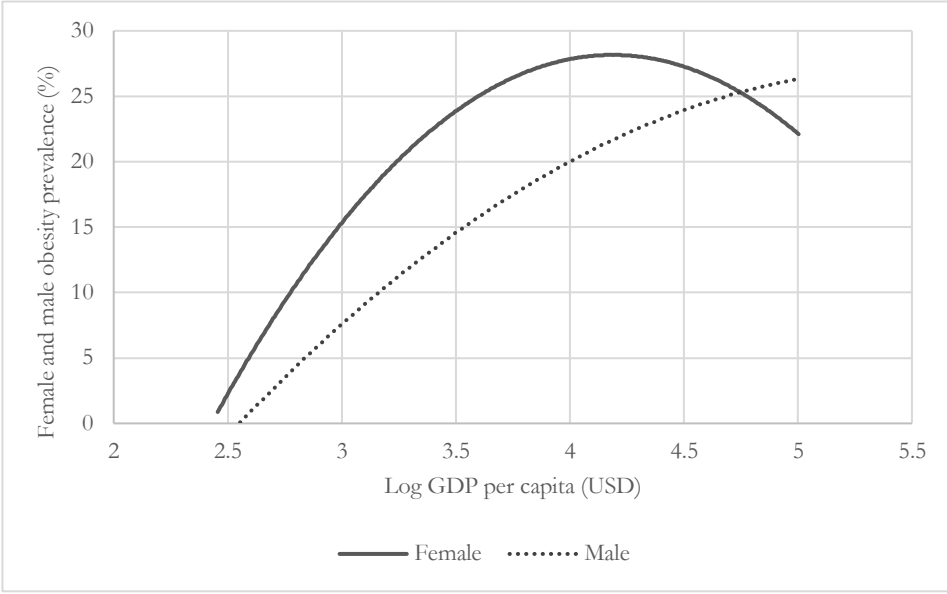
Figure 6 | Evolution of the average global obesity rate and per capita income (simple average and population-weighted average) 1976-2016



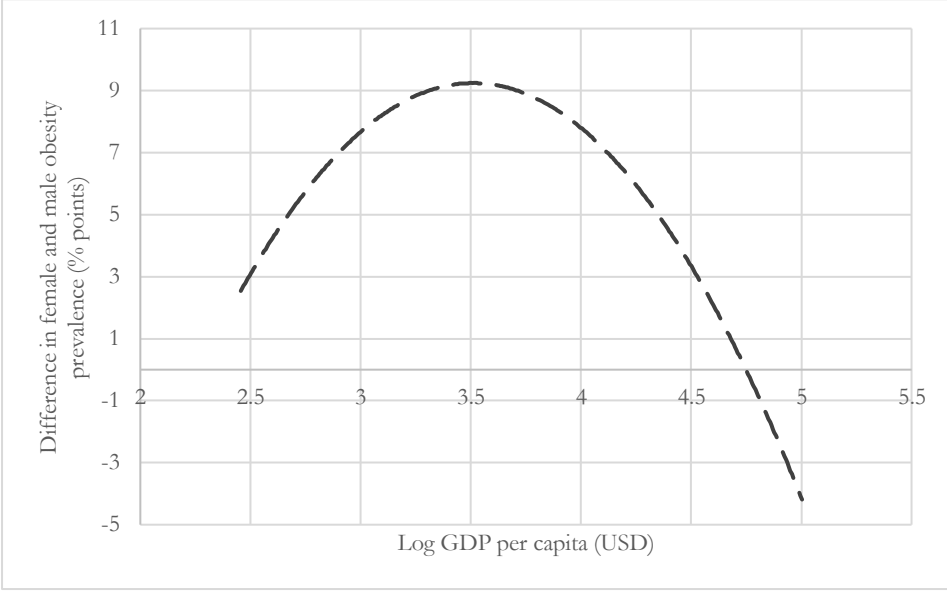
Source: WHO (1976, 1986, 1996, 2006, 2016) and WB (1976, 1986, 1996, 2006, 2016)

Figure 7 | Gender differences in obesity and its relationship with GDP per capita

7A: Average male and female obesity prevalence and GDP per capita



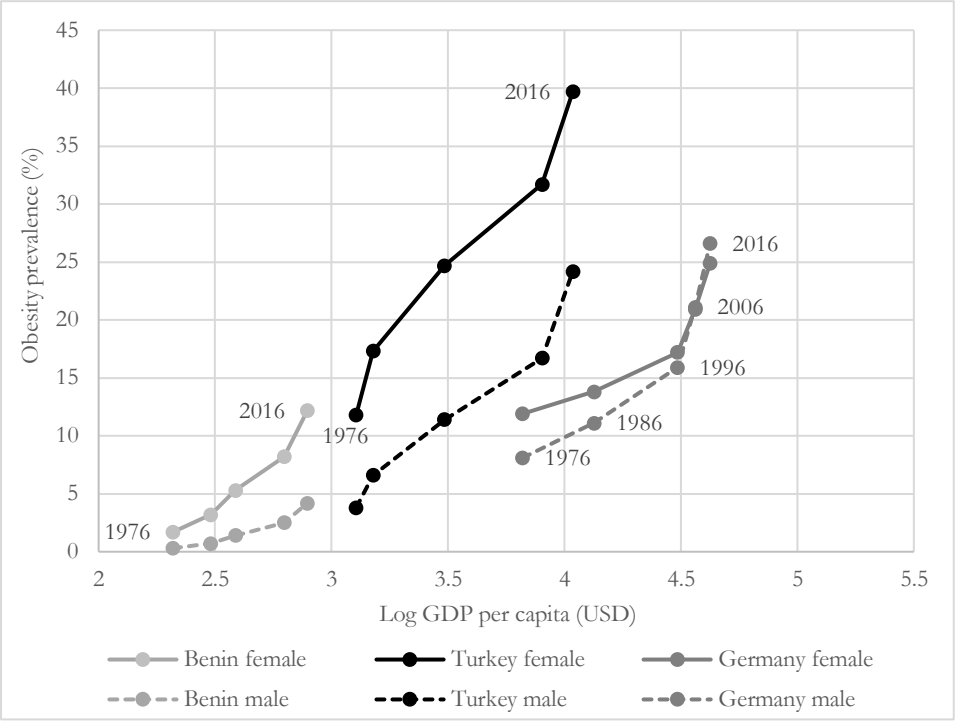
7B: Difference in average female and male obesity prevalence



Source: WHO (2016) and WB (2016) data

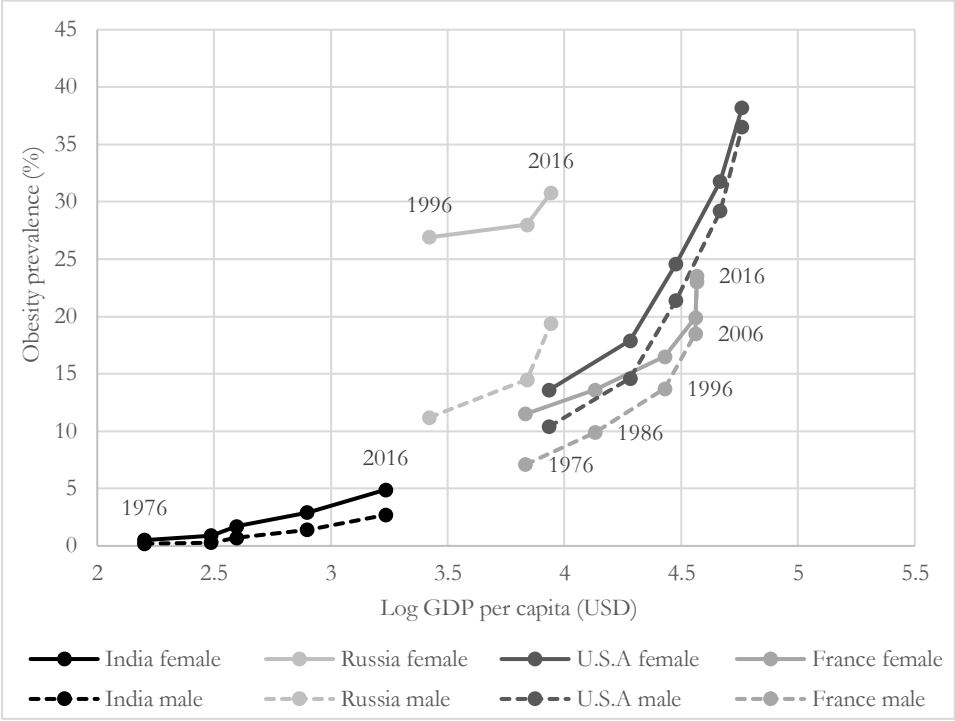
Figure 8 | Evolution of the gender obesity gap from 1976 to 2016

8A: Average female and male obesity prevalence in some low-, middle- and high-income countries (same as Figure 3)



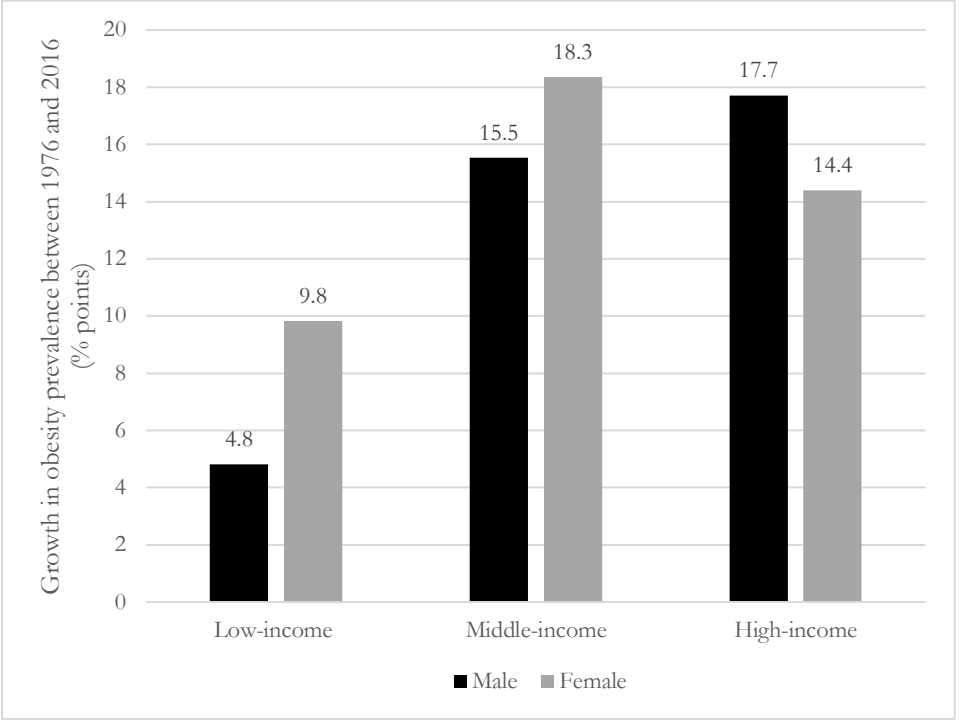
Note: Ghana, Dominican Republic and Spain are omitted to enhance clarity of figure. Ghana follows a similar trend as Benin, the Dominican Republic a similar trend as Turkey, and Spain a similar trend as Germany

8B: Average female and male obesity prevalence in some large countries



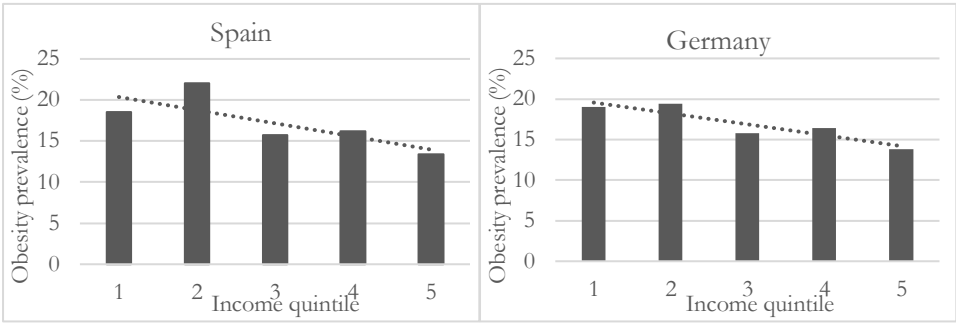
Note: China follows a similar pattern as India but with higher income growth over time
Source: WHO (1976, 1986, 1996, 2006, 2016) and WB (1976, 1986, 1996, 2006, 2016) data

Figure 9 | Growth in male and female obesity prevalence (% points) between 1976 and 2016 by country income group



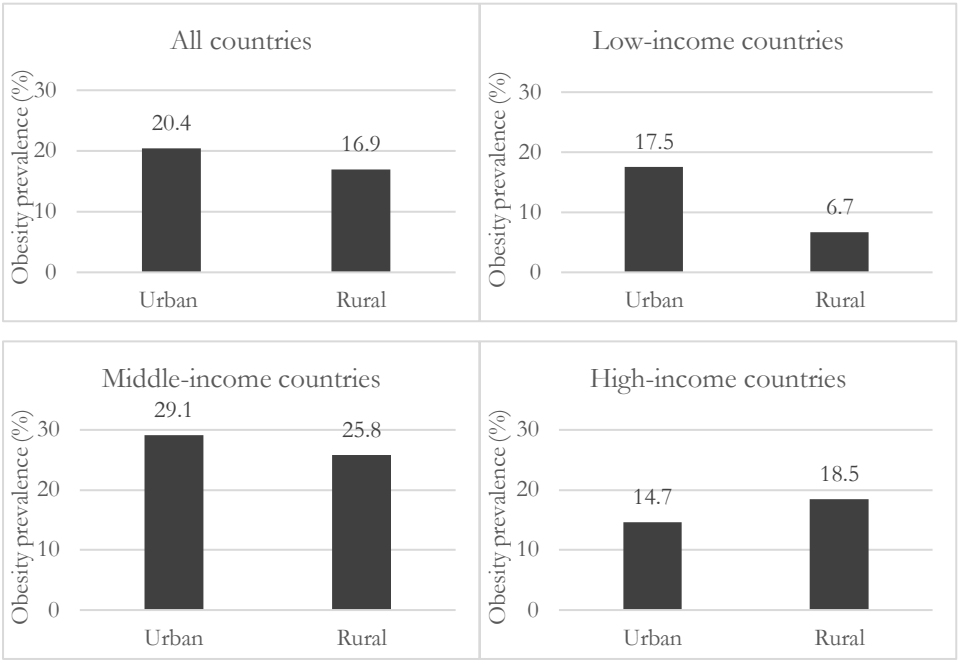
Source: WHO (1976, 1986, 1996, 2006, 2016) and WB (1976, 1986, 1996, 2006, 2016)
Note: Low-income, middle-income and high-income countries are classified by dividing the range of the log GDP per capita by 3. Low-income countries have a log GDP per capita lower than 3.3 (GDP per capita around 2,000 US$), middle-income countries between 3.3 and 4.2 (GDP per capita around 16,000 US$) and high-income countries above 4.2.

Figure 10 | Within-country male obesity prevalence and income



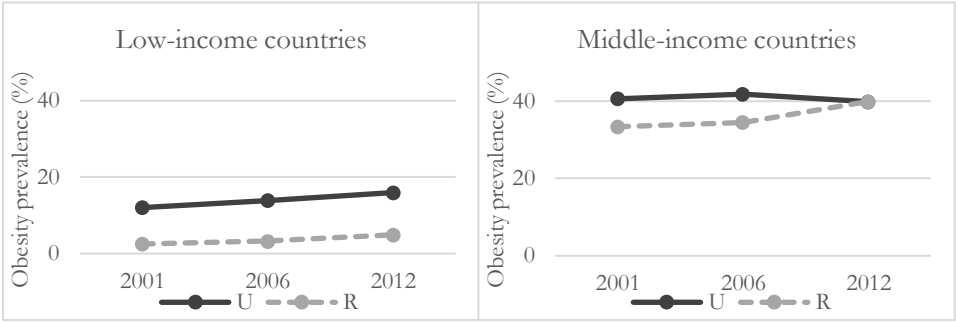
Source: European Health Interview Surveys 2014

Figure 11 | Obesity prevalence (%) in rural and urban areas in 2014



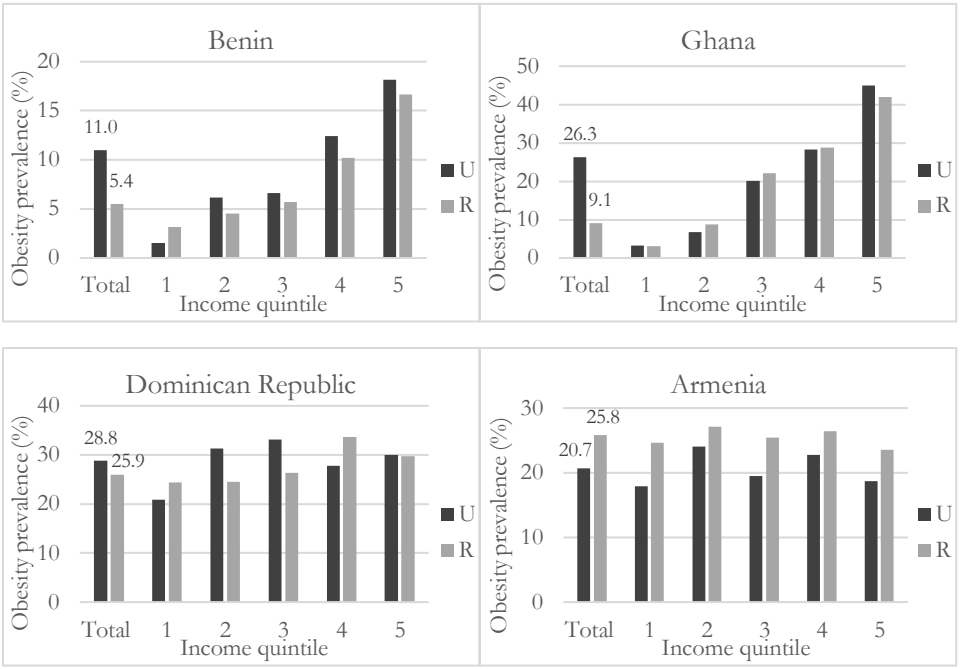
Source: Demographic and Health Surveys 2012-2014 (Low- and middle-income countries). European Health Interview Surveys 2014 (High-income countries)

Figure 12 | Change in female obesity prevalence (%) in rural and urban areas, 2001-2012*



Source: Demographic and Health Surveys (Low- and middle-income countries).
* These data are only available for females in low- and middle-income countries.

Figure 13 | Within-country distribution of female obesity prevalence by income group for rural and urban areas*



Source: Demographic and Health Surveys (Benin 2011, Ghana 2014, Dominican Republic 2013, Armenia 2015).

* These data are only available for females in low- and middle-income countries. Data for Turkey were not available to compare with Figure 2 – Armenia also falls in the middle-income category.

1.10 Tables

Table 1 | Relationship between GDP per capita[a] and obesity prevalence: regression results

		(1)	(2)	(3)	(4)
	Variables	All countries	Low-income countries	Middle-income countries	High-income countries
A. Total Obesity[b]	GDP per capita	0.0274***	0.239**	0.0271	-0.00245
		(0.00817)	(0.105)	(0.0474)	(0.00251)
	GDP per capita^2	-3.19e-05***			
		(1.08e-05)			
B. Male Obesity	GDP per capita	0.0311***	0.185**	0.0258	0.00204
		(0.00721)	(0.0885)	(0.0467)	(0.00239)
	GDP per capita^2	-3.08e-05***			
		(9.55e-06)			
C. Female Obesity	GDP per capita	0.0265***	0.332***	0.0133	-0.00601**
		(0.00955)	(0.122)	(0.0535)	(0.00298)
	GDP per capita^2	-3.53e-05***			
		(1.26e-05)			
	Regional Fixed Effects[c]	Yes	Yes	Yes	Yes
	Obs.	178	59	59	60

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
[a] GDP per capita has been divided by 100
[b] The dependent variable is total obesity among adults (A), male obesity among adults (B) and female obesity among adults (C). Data are from the World Health Organization (2016) and the World Bank (2016)
[c] Regional effects for Asia, Africa, North America, Central America, South America, Oceania, the Middle East, Pacific Islands and Europe as a reference category.

Table 2 | Share of the 20% poorest in total obesity prevalence

Country	Share of 20% poorest in obesity (%)
Ghana	2.8
Benin	6.5
Dominican Republic	15.9
Turkey	21.4
Germany	25.9
Spain	26.9

Source: WHO (2016)

Table 3 | Prevalence of stunting over time by country income category (% children under 5 years old)

Income category	1990	2000	2010	2016
Low income	54.1	47.0	39.9	35.9
Middle income	43.8	35.4	27.3	23.0
High income	4.1	3.4	2.8	2.5

Source: World Bank Database

Table 4 | Summary

	Cross-country obesity distribution	**Within-country obesity distribution**	**Gender obesity gap**	**Obesity over time**	**Urbanization and obesity**
Low-income countries	Increasing with income	Highest among richer groups	Female obesity higher than men	Slow growth	Highest in urban areas
Middle-income countries	Constant with income	Evenly distributed	Female obesity much higher than men	Strong growth	Evenly distributed
High-income countries	Decreasing with income	Highest among poorest groups	Female obesity same as men	Medium growth	Highest in rural areas

Chapter 2. Child health across the rural-urban spectrum*

2.1 Introduction

Developing countries are urbanizing rapidly. Nowhere is this phenomenon as pronounced as in sub-Saharan Africa (SSA), where annual urban growth rates have been around 3.5% for the past two decades and projections expect this trend to continue until 2050 (UN Habitat, 2014). This demographic shift over time from a primarily rural- to a primarily urban-based population will have profound implications across many dimensions of life. This paper looks at one such dimension, child health.

It is well-documented that children living in urban areas in developing countries score, on average, better on a range of health outcomes compared to children in rural areas (e.g. Van de Poel et al., 2007; Firestone et al., 2011). The main outcome of interest in this paper is the prevalence of child stunting, which is widely used as an indicator of adverse nutritional and health outcomes among this population group. Stunting can lead to an array of cognitive and physical problems, more severe illnesses and in some cases premature death (Peeling & Smart 1994; Pollitt, 1995; Grantham-McGregor et al., 2000; Berkman et al., 2002). This in turn leads to educational difficulties (Lozoff et al., 2000; Glewwe et al., 2001; Caulfield et al., 2006; Luo et al., 2012), lower future incomes (Bobonis et al., 2006; Halterman et al., 2001), increased health costs (Shorr et al., 2008) and decreased life expectancies, thus affecting a region's economic climate.

Research has shown that stunting is more prevalent in rural compared to urban areas (Von Braun, 1993; Menon et al., 2000; Smith et al., 2005; Amare et

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al., 2018).[10] Some work explores heterogeneity in rural areas. Using data on 23 sub-Saharan countries Headey et al. (2018) find that children in rural communities are more likely to be stunted and have worse dietary outcomes compared to children in urban communities, with children living in more remote rural areas experiencing only a small nutritional penalty.

That child health is better in urban areas is cause for optimism in an urbanizing Africa. But this gives little guidance to policy makers needing to decide on urban investments and, at the margin, which kind of urbanization to promote in their countries. This is an important lacuna, not in the least because choices made now will lock countries into a specific urbanization model for decades to come.[11]

Furthermore it is *a priori* unclear which trend, if any, child health is expected to follow across the urban continuum. Urbanization has been identified as an important driver of the "nutrition transition", through which dietary patterns and levels of physical activity are undergoing profound changes. While food insecurity and undernutrition are more common in rural areas, urban areas suffer more from dietary excess, which, exacerbated by sedentary lifestyles, leads to higher levels of obesity and an elevated prevalence of nutrition-related noncommunicable diseases (see for example Doak et al., 2005; Hawkes, 2008; Popkin, 1999; 2001). Cockx et al. (2018) discern a shift away from traditional staples towards more conveniently consumed, high-sugar or prepared foods when rural dwellers move to an urban environment in Tanzania, an effect that is more pronounced for those moving to cities compared to those moving to smaller towns. These findings indicate that diet quality can be highly varied between different types of urban areas. Calorie requirements may be fulfilled, yet micronutrient deficiencies may still be prominent.

High (and rising) urban incomes play an important role in mediating these effects (Hirvonen, 2016), but could be associated with a host of other pathways

[10] Urban areas also perform better on an array of other health indicators. Some studies find wasting, or an inappropriate weight-for-height, to be less common in urban areas (Sastry, 1997), however not all studies find a clear difference in this measure (Smith et al., 2005; Amare et al., 2018). Children are also more likely to be underweight in rural regions, indicated by a lower weight-for-age (Ruel et al., 1998). Anaemia is also more common in rural compared to urban areas in Bangladesh and Ghana (Ahmed, 2000; Ronald et al., 2006).

[11] Recent research has highlighted one interesting dimension in which this choice needs to be made: whether to invest in urbanization through large cities or through small towns (Christiaensen et al., 2013; Ingelaere et al., 2018). Secondary towns have come out quite favourably in this strand of the literature. Secondary towns are found to be positively associated with economic growth (Dorosh & Thurlow, 2013), inclusive growth (Christiaensen & Todo, 2014), employment opportunities for the poor (Glasser & Raich., 2008), poverty reduction (Christiaensen et al., 2017; Barrett et al., 2017; Mellor, 2017; Christiaensen et al. 2019; Kanbur et al., 2019) and creating opportunities in the surrounding rural areas (Berdegue et al., 2014, Vandercasteelen et al., 2017).

through which child health is affected. Increased income instigates higher opportunity costs of staying at home which creates a trade-off with parental time in caring for children. The opportunity cost of staying at home may be largest in the most urbanized areas. The greater consumption of processed and prepared foods in urban areas has been linked to the opportunity cost of women's time (Atkinson, 1992; Tinker, 1997), especially as consumers perceiving time-scarcity try to reduce time intensive household tasks, such as cooking (Celnik et al., 2012). Indeed, Kulwa et al. (2006) find a significant negative correlation between height-for-age z-scores of children and the number of hours per day mothers worked outside the home. Add to this that people tend to work far from home (Ruel et al., 2008) and that large agglomerations suffer from traffic jams and long commutes (Henderson, 2002). All these factors may influence child care and nutritional practices.

Finally there are large differences in the supply-side environments between rural and urban regions, and across various types of urban centres, with diverging access to water, sanitation and healthcare. Healthcare and other social facilities are generally more readily available in urban regions (UNCHS, 2001; Montgomery et al., 2013). Nevertheless, the soar in urbanization in sub-Saharan Africa may not have been given adequate time to provide sufficient sanitation and livelihood opportunities (Fotso, 2007). Clean water and appropriate waste disposal also experience further pressures from a rapidly growing urban population (Ruel et al., 2008; Crush et al., 2011). It is generally believed that healthcare and sanitation conditions are better in urban compared to rural regions yet these may be affected negatively by increasing migration. There is still no clear consensus on how cities of various magnitudes impact health institutions and sanitation.

Very little insight is given into how this plays out empirically as throughout the health and nutrition literature urbanization is usually observed and analysed as a binary construct, with a simple rural-urban classification. Our paper will link Demographic and Health Survey (DHS) data on 40,000 children, from ten countries in East Africa to satellite data of nighttime lights. Nighttime light data has been used to measure urbanization as light intensity increases from rural to more urbanized areas (Henderson et al., 2003; Burchfield et al., 2006; Sutton et al., 2010; Zhang & Seto, 2011; Donaldson & Storeygard, 2016). There are a number of advantages to nighttime lights. The first is that they provide a plausible continuous measure of the degree of urbanization and economic activity. Secondly, they provide a definition of urbanization that is consistent across different countries, something which administrative definitions cannot hope to

do. Thirdly, as we will show, there is quite some variation within urban areas with respect to the degree of nightlight emitted.

In a paper closely related to ours, Amare et al. (2018) identify that child nutritional outcomes improve and then level off as nightlight increases in Nigeria. Our study extends this work in three important ways. First, we expand the geographical scope to ten different countries in East Africa to test whether the patterns observed in Nigeria hold in other sub-Saharan African nations. Secondly, we enrich the nightlight data with population data on each urban area, allowing us to explore how population size and nightlights interact. Thirdly, we attempt to provide some evidence on the proximate drivers of these patterns by looking at trends in health inputs, maternal care, feeding practices and wealth across the urban spectrum.

We find that child stunting, first improves and then worsens at the highest levels of nighttime light. However, there are substantial disparities between countries. We identify three groups of countries, each following a specific trajectory. The first group, including countries like Burundi and Zimbabwe, do not have any nighttime light values in the upper ranges. Here we simply observe a linear downward trend, similar to all other countries across this area of support. The second group, presenting the most common trajectory, finds that stunting first decreases and then levels off as nighttime light intensity increases. Lastly, two countries, namely Kenya and Zambia, follow the overall evolution found for East Africa, where stunting first decreases across the lower ranges of nighttime light and then increases again at the highest levels of nighttime light.

We then use a new dataset from Africapolis (2018) to obtain population estimates and identify city types for each urban agglomeration in our data. Nighttime lights vary both within agglomerations and across agglomerations of similar sizes, giving us the necessary variation to disentangle the effect of nighttime lights from that of population size. We find that the increase in child stunting in the brightest areas comes from the largest cities of over 1 million people.

We then look at plausible mechanisms through which these effects take place. While there is no source of exogenous variation available to identify the effects, we gain insights from the extensive literature on child health to see which well-established determinants of child health evolve similarly with urbanization. First, we consider health inputs such as sanitation, clean water and access to healthcare, which have been shown to contribute greatly to child health (Smith, 1999; Marmot, 2006). Second, we look at infant and young child feeding practices, also important determinants of child nutrition and health (Black et al., 2008; WHO, 2009). Sanitation and healthcare access consistently improve with nighttime lights, which likely contributes to the decrease in child

stunting but does not explain the upturn at the highest levels of urbanization. Child feeding practices, however, follow the same initial improvement, but then deteriorate at the highest nightlight levels, mirroring the rise in child stunting in these areas.

While healthcare access, sanitation and child feeding practices are important determinants of child health, they remain proximate causes, which may, in themselves, have deeper root causes. However, as their importance for child health has been clearly established in the health literature, we are quite confident that they are part of the causal chain. We also look at how maternal and household characteristics vary across the urban spectrum and weigh up to what extent increasing wealth and other changes could account for the observed patterns. We find that the deterioration in child stunting rates is particularly pronounced for the highest wealth quartiles.

Section 2.2 of this paper will describe the data used in our analysis, section 2.3 presents the main results and section 2.4 discusses pathways. Section 2.5 explores heterogeneity across these pathways and section 2.6 concludes.

2.2 Data

2.2.1. Health outcomes and pathways

The data used in this paper come from the Demographic and Health Surveys phase VI and VII (DHS). We use child health outcomes, healthcare access and sanitation indicators, and nutritional inputs for 40,324 children between 24 and 59 months old in ten countries in East Africa[12]. Following recommendations by Alderman and Heady (2018), we exclude children younger than 24 months as any potentially harmful effects on height will not have manifested completely before this age, potentially leading to attenuated coefficients. Our primary health outcome is child stunting, which we define as a child having a height-for-age z-score (HAZ) two standard deviations below their reference group. Stunting indicates that a child has been unable to reach their full potential both physically and mentally due to chronic malnutrition.

[12] Burundi, Kenya, Ethiopia, Malawi, Mozambique, Rwanda, Tanzania, Uganda, Zambia and Zimbabwe.

The DHS also provide information on at least three direct determinants of child health: sanitation, healthcare access and nutritional inputs. First, for sanitation we know whether the household members have access to clean water[13], whether they have a proper toilet[14] available, and whether they dispose of child waste properly[15]. Second, for health facility access we know whether or not the respondent reports the distance to a health facility to be an impediment.

The third health determinant, feeding practices, are calculated based on the World Health Organization's (2008) infant and young child feeding practices (from hereon called feeding practices). These feeding practices are key indicators identifying whether babies and young children are receiving a fulfilling diet. Proper feeding improves child survival as well as optimal physical and mental development, especially during the crucial years between birth and 2 years of age. Current global statistics on proper feeding practices (UNICEF, 2018) are striking with only 2 out of 5 children exclusively breastfed below the age of 6 months and less than 75% of children being breastfed over the age of one. Numbers are even more concerning when it comes to solid food consumption with only 1 out of 2 children receiving the minimum meal frequency and only 25% of children reaching the minimum diet diversity required. Concentration on these feeding practices is therefore imperative in nutrition and child health research.

We use four indicators to measure feeding practices: a diet diversity score (Hirvonen, 2016), consumption of iron-rich foods, minimum meal frequency and continued breastfeeding after 1 years old. Importantly, DHS only collects food consumption data for the youngest child of the mother, conditional on the child having been born about 2 years prior to the survey. Due to our focus on children between 24-59 months old, this leaves few relevant data points on feeding practices for our sample of interest. To circumvent this we calculate average feeding practices at the cluster level, reflecting the typical feeding practices employed in the direct environment of the children in our sample.

We first calculate the diet diversity score, iron-rich food consumption and minimum meal frequency for the eligible youngest child of the mother. The diet diversity score, iron-rich food consumption and minimum meal frequency are measured for children between 6 and 23 months old. The diet diversity

[13] Access to clean drinking water is defined as drinking water directly piped into the dwelling or plot, coming from a public tap or tube well, a tanker truck or bottled water. This excludes all water sources that are not regulated or protected.

[14] Access to a proper toilet is defined as having access to a toilet with a flushing system or a ventilated improved latrine. This excludes other types of public latrines or no facility use.

[15] Disposing of child waste properly is defined as flushing waste down a toilet or latrine or thrown into the garbage. This excludes child waste being buried or not disposed of.

score states how many food groups were consumed from seven recommended food groups: grains, roots and tubers, legumes and nuts, dairy products, flesh foods, eggs, vitamin A-rich fruits and vegetables, and other fruits and vegetables (WHO, 2008). Iron-rich food consumption states whether the child received an iron-rich food the previous day. Minimum meal frequency states whether an infant received the minimum required meals according to their age[16]. We extrapolate these indicators to all children in the household to create feeding practice indicators at the household level. Then, we take cluster level averages for each indicator, which will be used in our analysis. Continued breastfeeding is derived from data on the duration of breastfeeding. This includes whether the child is older than 12 months and duration of breastfeeding was over 12 months or whether the mother is still currently breastfeeding and the child is older than 12 months. We then also take the average continued breastfeeding at the cluster level.

We further look at data on maternal education and earnings in cash, to gauge whether opportunity costs for women could adversely affect child feeding and therefore increase child stunting prevalence. A lower maternal education can also negatively impact child nutrition and health (Christiaensen & Alderman, 2004; Choudhury et al., 2019). To capture the influence of wealth, we use DHS data on asset ownership to construct a wealth index, allowing for cross-country wealth comparability. Following recommendations by Booysen et al. (2008), Traissac & Martin-Prevel (2012) and Ezzrari & Verme (2012) we use durable consumption goods to derive a wealth index using a multiple correspondence analysis. This method is most effective when using categorical instead of continuous variables. Our index is based on whether a household has electricity, owns a radio, television, refrigerator, bicycle, motorcycle, car/truck, has a concrete or tile floor, has at least a metal roof, has cement walls and uses non-wood cooking fuel. Access to water and toilet facilities are excluded as these will be captured separately through our healthcare and sanitation variables. The index is then normalized.

Finally, we complement the child stunting and pathway data with data on wasting and anaemia. Wasting is defined as having a measured weight-for-height z-score (WHZ) two standard deviations below the reference group median. Wasting is the consequence of undernutrition or severe disease, resulting in considerable weight loss. Anaemia constitutes a loss of red blood cells in the blood, a decrease in haemoglobin in the blood or a reduced ability for the blood

[16] Minimum meals are defined as 2 meals for breastfed infants between 6-8 months, 3 meals for breastfed children between 9-23 months and 4 meals for non-breastfed children between 6-23 months.

to carry oxygen. We create a dummy for whether the child is anaemic or not from the DHS provided data on child anaemia levels.

2.2.2. Nighttime lights

In order to establish the relationship between child health and urbanization, we use satellite nighttime light data as a proxy for urbanization. Recent studies focus on continuous and disaggregated indexes capturing micro-level variations due to the urbanization process (Van de Poel et al., 2012). Nighttime light data has the ability to capture urbanization as light intensity increases from rural to urban areas (Henderson et al., 2003; Sutton et al., 2010; Donaldson & Storeygard, 2016). A study by Zhang & Seto (2013) furthermore finds that nighttime lights are 93% accurate in predicting urban clusters, with the main issue being over-glow, now corrected for in recent data. Nighttime lights are also highly correlated with economic activity (Henderson et al., 2012), population (Sutton et al., 2003) and built environment (Lu et al., 2008). A particular advantage is that we can distinguish between various types of urban areas and between different parts of the same urban agglomeration.

The nightlight data used in this paper stems from the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB), collected jointly by NASA and the NOAA. The VIIRS DNB data provide several advantages to the previously used Defense Meteorological Satellite Program (DMSP) Operational Linescan System (OLS) data. There is a significant reduction in pixel footprint, lower detection limits, finer quantization, wider dynamic range and inflight calibration (Elvidge et al., 2013). The raw nightlight data is calibrated into units of average radiances in nW cm^{-2} sr^{-1}. The Demographic and Health Surveys include a composite of the VIIRS nightlight data in their geo-spatial dataset, which will be used in this paper. Each DHS cluster is represented by an average nighttime light number, calculated by averaging a 2km radius in urban areas and a 10km radius in rural areas.[17]

The nightlight values for our selection of countries range from 0 to 53.83. However, even for urban regions (defined by Africapolis) the raw nightlight data is severely skewed to the left, as observed in Figure A1, panel 1. 95% of the urban observations are found below a nightlight of 25.39. To smooth the distribution we use the inverse hyperbolic sine (IHS) transformation.[18] After applying this transformation we see the nightlight data is more evenly distributed and continuous, with a range from 0 to 4.68 (Figure A1, panel 2).

[17] DHS delineation for rural and urban areas is used here.

[18] A log transformation would have been an alternative. The advantage of the IHS transformation is that IHS is defined for zero values (Ravallion, 2017), which is important in the case of our large rural sample living in areas with a nighttime light of 0.

2.2.3. Urban population size

Figure 1 presents a visual overview of the nightlights in our sample. It is observed that capital cities, such as Nairobi and Kampala, and other large cities, like Dar es Salaam, are most illuminated. However, this does not mean that these cities are brightly lit in a spatially uniform way. Figure 2 shows the nighttime light distributions of the most populous city in each of the ten countries in our sample.[19] In places like Lusaka and Maputo there are no truly dark areas discernible, but in Nairobi, Dar es Salaam and Kampala the distribution reaches all the way to the lowest nighttime lights. This illustrates that even if population and nighttime lights are highly correlated, they do not portray the same aspects of the urbanization process. One advantage of nighttime lights over population data is its high spatial resolution. Whereas population data represent a single number for the whole city, nighttime lights inform us about disparities within a single city and across cities of similar sizes. Such disparities can be quite substantial, as shown in Figure 2.

We bring urban population size data into our analysis by mapping all DHS clusters to the nearest urban agglomerations identified in Africapolis (2018). Due to DHS displacements, we use a 5km buffer to determine whether a DHS cluster is found in an urban region. This cluster is then assigned the matching Africapolis data. Africapolis agglomerations are defined based on a spatial approach applying both a physical element (built-up area) and a demographic element (more than 10,000 inhabitants). An urban area is identified by combining satellite and aerial imagery with official demographic data from censuses and other cartographic sources. Africapolis provides estimates of total population and total built-up area. Using this data, it is useful to categorize the regions in our sample into 4 different groups: rural, small towns (ST) with a population under 100,000, big towns (BT) with a population between 100,000 and 1,000,000, and cities with a population over 1 million (Table 1, panel A). This gives an idea of the size of the urban areas in our analysis.

Another useful grouping is to separate the nighttime light values into three bins representing dark, medium and bright areas (Table 1, panel B). From Table 1, panel A, we can see that the 99th percentile of nightlight values in rural areas is 1.80, which we use as the cut-off value for dark areas. This means that (almost) all rural areas fall into the dark category of nighttime lights. But, as we saw in Figure 2, plenty of large cities also have areas categorized as dark. This is also evident from the average population size of dark areas, which falls at

[19] The nighttime light distributions are derived from the DHS sample in each location.

about 250,000 people (Table 1, panel B), much higher than an Africapolis defined rural area of less than 10,000 people.

Another natural cut-off is the 99th percentile of the nightlight values for big towns (with a population of 100k – 1m), which is 3.62 (Table 1). Nightlight values above this occur (nearly) only in the very largest cities with over 1 million people. We call this category bright. Table 1 shows that although cities have a relatively high nightlight value, at on average 3.11 (Table 1, panel A), this value is much lower than when only observing the brightest regions in our sample, with an average nighttime light of 4.07 (Table 1, panel B).

Finally, we can combine population and nighttime light data to create the following combined bins: rural dark, small town dark, small town medium light, big town dark, big town medium light, city dark, city medium light and city bright. Table 2 shows how the sample of 40,324 children is spread across these 8 bins.

2.3 Urbanization and child health

2.3.1. Main result

Table 1, panel A, shows that child stunting levels go down as we move from rural areas, to small and big towns, to large cities. More surprisingly, perhaps, is that Table 1, panel B, shows there is no such downward trend across nighttime lights. Here the darkest areas have the highest stunting levels at 41.34%, but medium lit areas have lower stunting levels (25.46%) than the brightest areas (30.58%).

To formalize the descriptive statistics depicted in Table 1, panel B, we use nonparametric and unconditional regressions to characterize the relationship between urbanization, proxied by nighttime light, and child stunting. Figure 3 displays the probability that a child is stunted across the spectrum of urbanization. Child stunting decreases with nighttime lights on the darker left-hand side of the distribution, but then increases again on the brighter right-hand side of the distribution, creating a U-shaped evolution. The two vertical lines show the 99th percentile cut-off values for rural areas and big towns, beyond which we can be sure there are virtually no rural areas and no big or small towns, respectively. We see that the downward sloping part of the graph occurs at nighttime light values typical in rural areas, the lowest levels occur at nighttime light values typical for towns and some city areas, while the upward sloping section of the graph is restricted to nighttime lights values that occur only in large cities.

As was clear from Section 2.2, towns and cities also have many darker areas. It is therefore informative to repeat the figure excluding rural observations

(clusters with less than 10,000 people, defined by Africapolis). We do this in Figure A2 (Appendix), where the U-shaped curve is maintained for children living in urban regions. Even within urban areas child stunting first improves and then worsens with nighttime lights.

In Table 3, column 1, we show the results from a linear probability model explaining whether or not a child is stunted on the nighttime light categories delineated in Figure 3. In panel A we see that stunting levels are 16 percentage points higher in dark areas compared to medium lit and bright areas. In panel B we see that the brightest areas have stunting levels that are 8 percentage points higher than the medium lit areas and 9 percentage points lower than the dark areas, confirming the U-shape in Figure 3.

2.3.2. Urban heterogeneity – population size

Population size is a commonly used proxy for city size. The correlation between urban population and emitted nightlights is positive, but not perfect. Two equally bright areas may be located in urban agglomerations of very different sizes. Similarly, within the same urban agglomeration there will be variation in the intensity of light across space.

In Table 1, panel A, we see that child stunting decreases as population increases. Rural areas have an average child stunting rate of 43.29%. These levels are lower for small and big towns, at 31.81% and 29.12% respectively. Cities have the lowest levels of child stunting, at 23.10%. In the first panel of Figure 4, we regress a dummy indicating that a child is stunted on the population size categories from Table 1, panel A. The omitted category in this regression is cities[20]. Confirming the observations from our descriptive statistics in Table 1, we find that child stunting decreases gradually with population size and children living in cities are least likely to be stunted (also found from the polynomial association between child stunting and population size in Figure A3, Appendix).

Conversely, Table 1, panel B, shows that child stunting is lowest in medium-lit regions, at 25.46% compared to 41.34% in dark areas and 30.58% in bright areas. This finding is formalised in the second panel of Figure 4, where bright regions fare better than dark regions but worse than medium-lit regions. Combining both population and nightlight categorizations, Table 2 shows that child stunting is highest in rural, dark regions, at on average 43%. Dark regions also have the highest stunting levels in small and big towns. However, in cities, the brightest regions have the highest prevalence of child stunting, at about 31%,

[20] Throughout the analysis we will use the most populous and/or bright areas as the omitted category.

compared to 28% in dark city regions and 19% in medium lit city regions. Medium-lit city regions have the lowest overall levels of child stunting. We use these same combined population and nightlight categories in the third panel of Figure 4 and regress child stunting levels on the interacted dummies, using the bright city regions as the omitted category. We see that medium lit areas in cities have the most favourable child stunting outcomes, suggesting that the upward sloping section of the U-shape in Figure 3 is primarily driven by worse child health outcomes in the brightest areas of cities.

In order to ascertain whether these effects hold within urban regions as well as across urban regions, we run agglomeration fixed effects regressions of child stunting on the population and nightlight categories for each type of urban region. Medium lit areas are omitted in panel 4 and 5 and bright areas are omitted in panel 6. Panel 4, Figure 4, shows that dark regions in small towns have higher levels of child stunting than medium lit areas within the same small town. However, dark areas within big towns do not significantly differ from medium lit areas within those same big towns (panel 5), and dark or medium lit areas within cities do not significantly differ from bright areas within those same cities (panel 6). We therefore cannot confirm that differences hold within these big towns and cities.

2.3.3. Urban heterogeneity – Disparities between countries

The region-wide evolution of child stunting with nighttime lights in East Africa may hide some disparities between countries. Therefore, Figure 5 presents country specific polynomial associations. These clearly indicate that the relationship between stunting and urbanization is far from uniform across East Africa.

Before we discuss this diversity, one consistent pattern for all countries is the rapid improvement in stunting across the darker regions on the left-hand side of the graphs. Children living in areas with nighttime lights under 1.80 have the highest stunting rates. This category contains 99% of all rural observations, but also some dark urban locations (see Table 1 and 2). Table A1 further explores this relationship by regressing a dummy for nighttime lights below 1.80 and above 1.80 on the probability a child is stunted (panel A). Table A1, panel A confirms the findings from Figure 3 and 5, that children are less likely to be stunted when nighttime lights are higher than 1.80.

After the initial decrease in stunting there are three main patterns to be discerned (Figure 5). First, in Burundi and Zimbabwe nightlight values do not reach the highest levels. Here, child stunting levels simply decrease with urbanization. Ethiopia follows the same pattern, although reaching higher levels of

nighttime lights. Second, in Kenya and Zambia stunting levels-off and then increases again, following the U-shape identified in Figure 3. Third, and the most common trajectory, is that child stunting levels stagnate after a certain nighttime light value. This pattern holds for Malawi, Mozambique, Rwanda, Tanzania and Uganda.

Table A1, panel B presents the regression results for these patterns. Here, we split the medium light category into three subgroups[21] to capture the maximum nighttime lights for all countries individually. As observed from Figure 5, the range of nighttime lights varies greatly across countries. It is thus important to identify the omitted i.e. highest nightlight category properly. Burundi, for example, is a relatively dark country, with the highest nighttime lights ranging between 1.80 and 2.40. From Table A1 panel B, we can determine whether nighttime light categories lower than the brightest category have a significantly positive or negative relationship. Kenya and Zambia have a significantly lower probability of stunted children at a lower nighttime light category than the most luminous one. Countries like Burundi and Zimbabwe have a linear relationship between stunting and nighttime lights, and countries including Ethiopia, Malawi, Mozambique, Rwanda, Tanzania and Uganda have an at first decreasing relationship between stunting and nightlights, which then becomes insignificant. For these countries stunting improves as nighttime lights increase, and then levels off, with less differences between urban regions themselves.

2.3.4. Wealth heterogeneity

Average child stunting levels across the urban spectrum may also disguise how this relationship evolves at different wealth levels. It is therefore useful to look at the evolution of child stunting with urbanization for several wealth categories (Figure 6). Here we divide our wealth index into quartiles. The poorest and poor-mid 25% of households are mostly found in rural or dark areas. This explains the wide confidence intervals towards the right-hand side of panel 1 and 2 of Figure 6. On average, children from these households experience the highest levels of stunting, at about 45%.

Children from mid-rich households are slightly less likely to be stunted than children from poorer wealth categories, however average levels are still around 40%. For this wealth category, we find that stunting levels decrease but then rise again to an average of 50% at the highest levels of nighttime lights. Child stunting levels for the richest 25% of our sample experience a similar evolution

[21] The subgroups are calculated by dividing the nighttime lights between 1.80 and 3.62 into three equal sections. Splitting the medium light category gives us a clearer overview of the range of nighttime lights per country.

to the mid-rich wealth category, although average stunting rates are lower. Children in the richest wealth category have, on average, a 25% probability of being stunted in dark areas, 22% probability in medium lit areas and 29% probability in bright areas. We find that it is mainly children coming from mid-rich and rich households that are driving the upturn in child stunting found in Figure 3.

2.4 Pathways

Thus far, the analysis has shown that child health first improves with urbanization, but then worsens at the highest levels, in the largest cities. The data show that the improvement across the lower levels of urbanization is true for all ten countries considered, but that the increasing levels of child stunting at the highest urbanization levels are mainly driven by Zambia and Kenya. The effects are primarily visible for children from the two richest quartiles.

Our analysis continues with a two-pronged approach. First, in Figure 7, we plot urbanization levels against some of the known determinants of child health for which we have data. This includes data on healthcare access and sanitation, feeding practices, maternal characteristics and wealth, as explained in Section 2.2. We are looking for variables that follow the same trend of initial improvements and then worsening. Even if these variables may not be root causes, their role in determining child health has been well-established in the medical literature and we can therefore be confident that they play an important role within the causal chain. In this way, we can uncover some plausible channels through which urbanization is affecting child health.

Second, in Table 3, we run several linear probability regressions that assess the effect of nighttime lights on the probability that a child is stunted. In panel A, we measure child stunting through the dummy $Stunted_{ic}$, which takes the value 1 when child i, in cluster c is stunted and 0 otherwise. $Dark_c$ represents whether cluster c has a nighttime light below 1.80, the left most region in Figure 3. The regressions are first run without any controls. We then add a set of basic control variables represented by the vector X_{ic} containing household size, the age of the mother, whether the household head is male and a full set of dummies to control for the child's gender, age (in months) and country. To this second specification we then add vectors for healthcare access and sanitation, H_{ic} (4 dummies indicating the household has a proper toilet, clean water, disposes of child waste properly and has access to a health facility), feeding practices, F_c (cluster level averages for diet diversity score, iron-rich food consumption, minimal meal frequency and continued breastfeeding), maternal characteristics M_{ic} (years of education of the mother and a dummy indicating she is earning cash income) and a constructed wealth index, W_{ic}. Details on the

included variables can be found in Section 2.2. The final regression includes all variables simultaneously, as follows

$$Stunted_{ic} = \beta Dark_c + \delta X_{ic} + \theta_1 H_{ic} + \theta_2 F_c + \theta_3 M_{ic} + \theta_4 W_{ic} + e_{ic}$$

where e_{ic} is the error term.

The first column in Table 3, panel A, repeats the result from the previous section showing that β>0. The second column shows that adding the basic control variables (X_{ic}) reduces the coefficient slightly from around 16.1 to 14.7 percentage points, but the difference between dark and medium to bright areas remains large and very significant. Section 2.4.1. to 2.4.4. will discuss how the size and significance of β varies when adding other controls to inform on whether these are likely pathways through which the initial improvement in child stunting happens.

Table 3, panel B, presents a similar set-up in which we investigate plausible pathways explaining the increase in child stunting on the right-hand side of Figure 3. We split the nightlight data up into three dummies, representing the three areas identified in Figure 3: dark areas with nightlights below 1.80 $(Dark_c)$, medium areas with nightlights between 1.80 and 3.62 $(Medium_c)$ and bright areas with nightlights above 3.62. Using the latter group as the omitted category, we build the regressions up in a similar way as before, with the final full regression as follows:

$$Stunted_{ic} = \beta_1 Dark_c + \beta_2 Medium_c + \delta X_{ic} + \theta_1 H_{ic} + \theta_2 F_c + \theta_3 M_{ic} + \theta_4 W_{ic} + e_{ic}$$

Here we are interested in β_1 and β_2. The pattern discussed regarding Figure 3 is one where β_1>0 and β_2<0. The first column in Table 3, panel B shows that stunting levels in dark areas are 8.8 percentage points above those in bright areas, while medium lit areas have stunting levels that are 9.5 percentage points lower than those in bright areas. Adding basic controls attenuates the difference between bright and medium lit areas, but not as much between bright and dark areas. In section 2.4.1. to 2.4.4. we will discuss how the coefficients change as we add the controls representing possible pathways.

2.4.1. Healthcare access and sanitation

The first row of Figure 7 provides polynomial associations between nighttime lights and sanitation, clean water and access to health care. These important health inputs are found to improve with urbanization. Households are almost 50 percentage points more likely to have an improved toilet in large cities and almost 100% of all high level urban households have access to clean water and

dispose of child waste properly. Health facilities are also considerably easier to reach, with only 50% of rural households stating that they have an easily accessible healthcare facility compared to 90% in cities.

When adding these sanitation and healthcare variables to the regressions for dark areas compared to the omitted group of areas with a nightlight higher than 1.80 (column 3 of Table 3, panel A) we see a much reduced coefficient, suggesting these factors are important in explaining the initial improvement in child stunting. Initially, child stunting levels are between 16 and 15 percentage points higher in dark areas than in areas with a nightlight higher than 1.80 (column 1 and 2 respectively). These differences reduce by 7-8 percentage points when controlling for healthcare access and sanitation.

Panel B, provides similar results for dark vs bright regions. Table 3, panel B column 3, shows that β_1 reduces in size and also loses significance. However, we see very little change in size or significance with respect to the coefficients measuring the difference between the medium and bright areas, β_2. This suggests, in line with Figure 7, that differences in sanitation and healthcare access do not explain the increased stunting levels in the brightest urban areas but can attribute to the improvement in child stunting from dark to brighter lit areas.

2.4.2. Feeding practices

Dietary quality is also a key determinant of child health outcomes and may differ across various levels of urbanization. The DHS data allow us to establish cluster level averages for feeding practices, which we can relate to cluster level nighttime light data. Figure 7, row 2, presents four key feeding practices, namely a diet diversity score (the score ranges from 1 to 7), a dummy for whether the child consumed iron-rich food, a dummy for whether they attained a minimum frequency of meals and a dummy for whether there was continued breastfeeding after 12 months old. Looking at the diet diversity score portrayed in Figure 7, we find that this pattern perfectly mirrors that of child stunting (Figure 3). Furthermore, iron-rich food consumption and minimum meal frequency follow similar patterns, with better consumption rates in medium lit areas and a dip in consumption in the brightest areas. Lastly, although relatively low across the board, continued breastfeeding decreases steadily as urbanization increases. This may be associated with higher time constraints and parental opportunity costs in cities (see next section).

Further evidence supporting the nutrition channel comes from child wasting and anaemia patterns across the nighttime light spectrum (Figure A4). Both follow the same pattern as stunting, but for anaemia we can clearly distinguish the U shape. The confidence intervals for wasting are too wide to conclude the

same.[22] Considering these findings, children most likely access sufficient calories (as evidenced by wasting), but the problem lies with the nutritional content of the food they consume (which the anaemia levels suggest).[23]

From the regressions in Table 3, we find that the feeding practice environment has a small impact on the differences in child stunting between dark and light areas. In panel A, column 4, the coefficient of interest drops from 14.7 to 13.5 percentage points when controlling for cluster level feeding practices. In panel B, the coefficients of interest essentially remain unchanged. This may be due to the fact that we use a coarse cluster level measure.

2.4.3. Maternal characteristics

On the one hand maternal earnings can represent an opportunity cost for a mother's time inputs, possibly having negative effects on children. On the other hand, they could imply more female-controlled resources and correlate with maternal characteristics that have a positive effect on child health, such as the mother's education. In the first panel of row 3, Figure 7, we see that the share of women who earn cash increases with nighttime lights. This share reaches a peak at a nighttime light of about 2, decreases slightly, then levels off. In row 3, panel 2 of Figure 7, we see that the average years of formal education also increases with nighttime lights. This variable follows a similar pattern to maternal earnings in cash.

When controlling for maternal earnings in cash and education levels, we find a substantial drop in the coefficient sizes for the regressions in Table 3, column 5. Including maternal characteristics reduces the difference in child stunting between areas with a nightlight below and above 1.80 by almost 6 percentage points (panel A). Panel B shows that when comparing dark and bright regions, child stunting differs by 4 percentage points when controlling for maternal characteristics, compared to 9 percentage points without these controls (column 2), as well as a drop in significance. The coefficient illustrating the increase in child stunting levels between medium and brightly lit areas, however, remains the same.

[22] It must be noted that wasting levels are generally quite low and so the lack of variability may influence this result.

[23] We call this suggestive evidence of the nutrition channel as there are several types of anaemia, some of which can also be due to non-nutrition related factors such as intestinal worms or internal blood loss. Intestinal worms are however more common in rural areas, so the fact that anaemia increases at the highest levels of urbanization is most likely related to undernutrition than other causes.

2.4.4. Wealth

Differences in health inputs such as sanitation, healthcare access, feeding practices and maternal characteristics undoubtedly play a role in explaining why we see such large differences across the urban spectrum. Yet, these in themselves may be driven by deeper rooted determinants, which also vary by level of urbanization, such as differences in wealth. Controlling for wealth is important as the literature commonly finds that stunting, as well as other nutritional outcomes, improve with wealth (Sahn, 1994; Christiaensen & Alderman, 2004), which also strongly increases with urbanization. This is also evident in our sample, shown by the positive relationship between household wealth and nighttime lights, row 3, panel 3 of Figure 7. Wealth differentials can also play a greater role in urban areas, due to larger disparities within the region (Menon et al., 2000). Asset poverty is expected to be especially important from the age of 24 months and older (Fotso et al., 2012).

Including the wealth index in the regressions has a significant impact on the coefficients. From panel A, we can see that adding wealth, completely explains away the difference in child stunting between dark and medium-bright lit areas (column 6). Compared to a child stunting difference of 15 percentage points in column 2, this drops to a 1 percentage point difference in column 6 and loses significance. When adding the wealth index into the regressions comparing the three levels of nighttime lights, we find that the coefficient for dark vs bright areas changes from a positive to a negative sign. The coefficient for medium vs bright areas increases and remains strongly significant. Once we consider wealth differences it becomes even harder to explain why stunting goes up in brighter areas. These findings align with our observations from Figure 5, showing that children from mid-rich and rich households mainly experience an increase in stunting levels at the highest levels of urbanization.

The final column in Table 3 adds all the variables to the model. This gives an insignificant urban-rural difference, but very little changes for the coefficient measuring the difference between medium-lit and bright regions. Nevertheless, it must be noted that even after adding all variables, our model can only explain 9% of the observed variation in child stunting rates of the sample.

2.5 Pathway heterogeneity

The U-shaped pattern of child stunting with urbanization was found to be driven by two countries and by the two highest wealth quartiles. It is therefore worth repeating the previous analysis specifically for subgroups of the sample defined along these lines.

2.5.1. Country disparities

As identified in Section 2.3.3, there are significant differences in child stunting outcomes and urbanization between countries. Therefore, we repeat our analysis from Figure 7 and Table 3 for two separate groupings of countries: Kenya and Zambia, and the rest (Burundi, Ethiopia, Malawi, Mozambique, Rwanda, Tanzania, Uganda and Zimbabwe).

First, Figure A5 and A6 mimic the structure presented in Figure 7. When solely analysing these patterns for Kenya and Zambia (Figure A5), we find that certain health inputs do not follow the continuous upward trend that was observed in Figure 7. Whether a household has an improved toilet decreases at the highest nighttime lights, and access to water stagnates after a certain level of urbanization. In general, feeding practices do not differ greatly between Kenya and Zambia and other countries, although minimum meal frequency is lower. Most noteworthy is that maternal education levels fall at the highest levels of nighttime lights and whether the mother earns cash is lower for these countries than for the others. Lastly, wealth levels are lower across the board and also increase at a slower pace with urbanization in Kenya and Zambia than for other countries. It may be that in Kenya and Zambia, the combination of lower maternal earnings in cash and lower educational levels, with a slower improvement in healthcare access, sanitation and wealth lead to worse health outcomes for children.

When reassessing the regression results for the split subsamples of countries, we find similar results. First, the main regression result from Table 3 panel B, column 1 and 2, does not hold when looking at countries excluding Kenya and Zambia (Table A2, panel B). When adding the basic controls, these countries experience improvements in child stunting levels as nighttime lights increase, confirming that children in Kenya and Zambia are driving the U-shaped results. Table A3 presents the regression results for Kenya and Zambia. As previously found, healthcare access and sanitation, feeding practices, maternal characteristics and wealth come out as pathways through which stunting levels decrease at lower levels of urbanization, but not for the increase at higher levels.[24]

2.5.2. Wealth disparities

As observed in section 2.3.4. and from Table 3, wealth has a profound influence on child stunting levels across the rural-urban spectrum. The patterns from

[24] Data limitations restrict the identification of drivers behind the upturn in child stunting in bright urban regions. Further data on food prices, supermarket availability and quality, child care alternatives and individual child feeding practices are needed.

Figure 7 are confirmed by regressions following the structure used in Table 3 panel B, but run for the separate wealth categories (Table A4). The results confirm that the increase in child stunting levels with urbanization are captured by the mid-rich 25% and the richest 25% of households. Children from the poorest 25% or poor-mid 25% show no significant difference in stunting levels across the three nighttime light categories. Children from mid-rich households, living in bright urban areas, are about 13 percentage points more likely to be stunted compared to those living in medium lit areas (Table A4, panel C). There is no significant difference between bright and dark area stunting levels. These patterns hold for the richest households, although the difference is reduced to about 8 percentage points. For the mid-rich households we find that maternal characteristics explain some of the differences in child stunting between medium lit and bright regions (Table A4, column 5, panel C). Coefficient β_2 drops by 2.6 percentage points and becomes insignificant, but the standard error changes very little.

Overall, the U-shaped pattern identified in Figure 3, and especially the increase in child stunting at the highest levels of nighttime lights, is driven by child stunting differences between medium and bright lit areas for the mid-rich and richest households. There is some suggestive evidence that this is related to maternal characteristics.

2.6 Conclusion

In East Africa child stunting is highest in rural areas, followed by small and big towns and is, on average, lowest in cities. We use nighttime lights data to look behind these agglomeration-level averages and find that child stunting first improves with nighttime lights but then deteriorates at the highest levels. This region-wide pattern hides important differences across countries. While in all ten countries child stunting decreases quickly at the lower levels of brightness, for some countries this trend continues linearly, for others it tapers off, and for some there is an increase at the highest levels of nighttime lights. It is mainly in bright areas of large cities that child stunting levels worsen again. Child growth is often best in medium-lit areas of big towns and cities. The increase in child stunting at the highest levels of urbanization is primarily driven by children from families with above-median wealth.

We seem to have a good understanding of why dark areas fare so much worse than medium lit and bright areas. Sanitation, water, healthcare access, maternal characteristics and wealth play a crucial role here. The most promising explanation for the increased stunting levels in the brightest areas compared to

the medium lit areas comes from the feeding practices data. Diet diversity, minimum meal frequency, continued breastfeeding and iron-rich food consumption all go down in the brightest areas. Even for countries where child stunting tapers off at the highest levels of nighttime lights, these feeding practices all decrease. This finding is strengthened by the fact that anaemia also increases in these areas. For policy makers this would suggest that targeted interventions on feeding practices can have high pay-offs in both rural and highly urbanized regions.

At the same time we are careful not to overstate that these are core drivers of the observed pattern, as controlling for feeding practices in a regression framework does not eliminate the measured gap. That said, feeding practices and parental characteristics seem like a very good place to start for future research on mediating factors. Our analysis only includes crude data on maternal earnings and cluster level data for feeding practices. Future research with better earnings and time use data could investigate the changing role of female employment, time allocation and changes in female-earned income across the urban spectrum and how this interacts with child health through pathways such as feeding practices.

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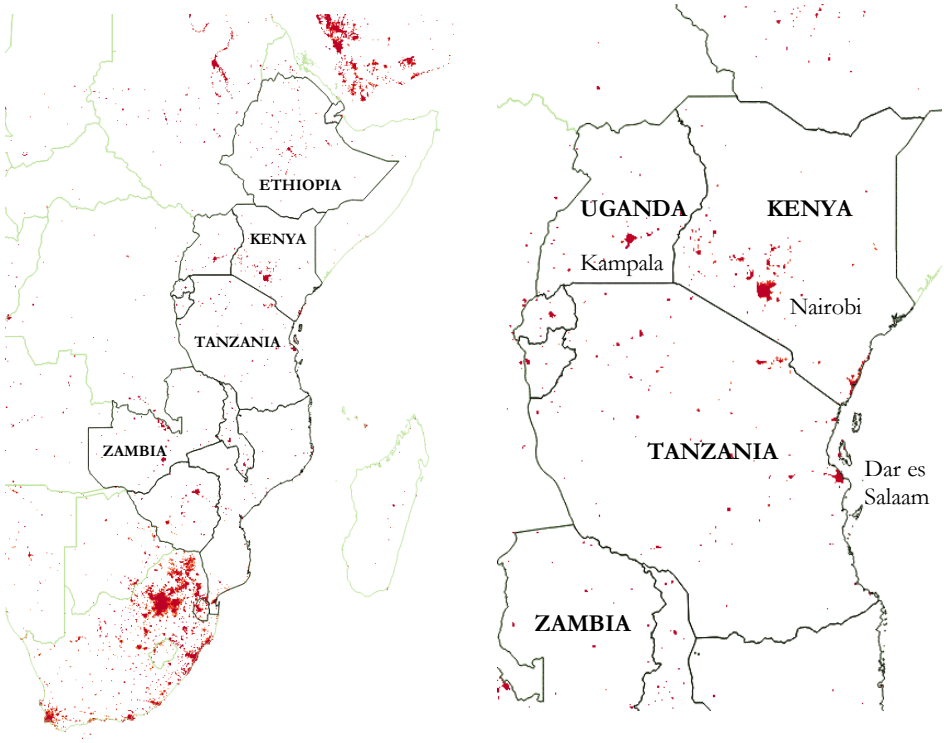
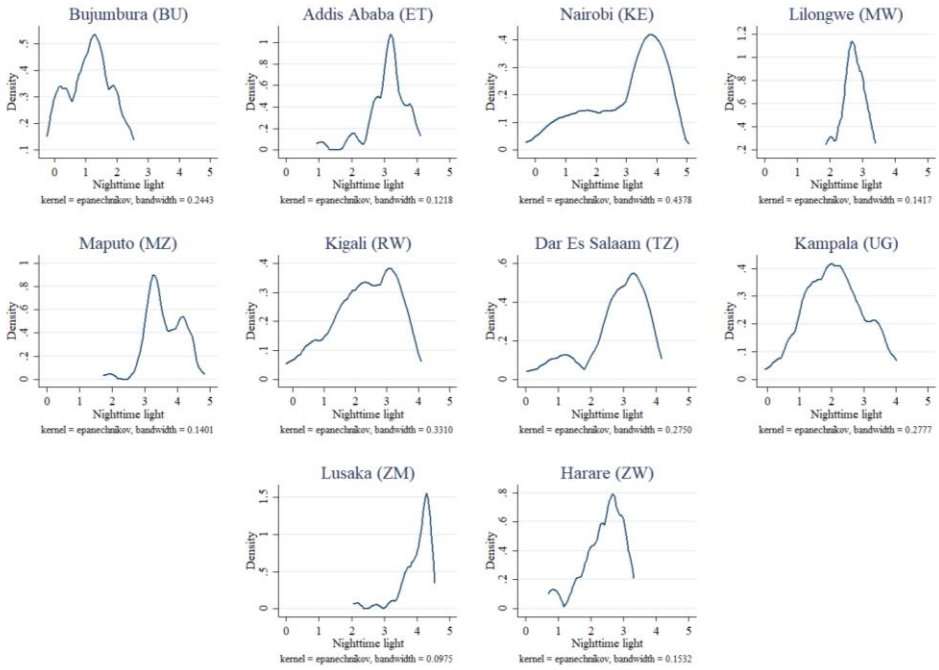
2.8 Figures

Figure 1 | Nighttime light projections for East Africa



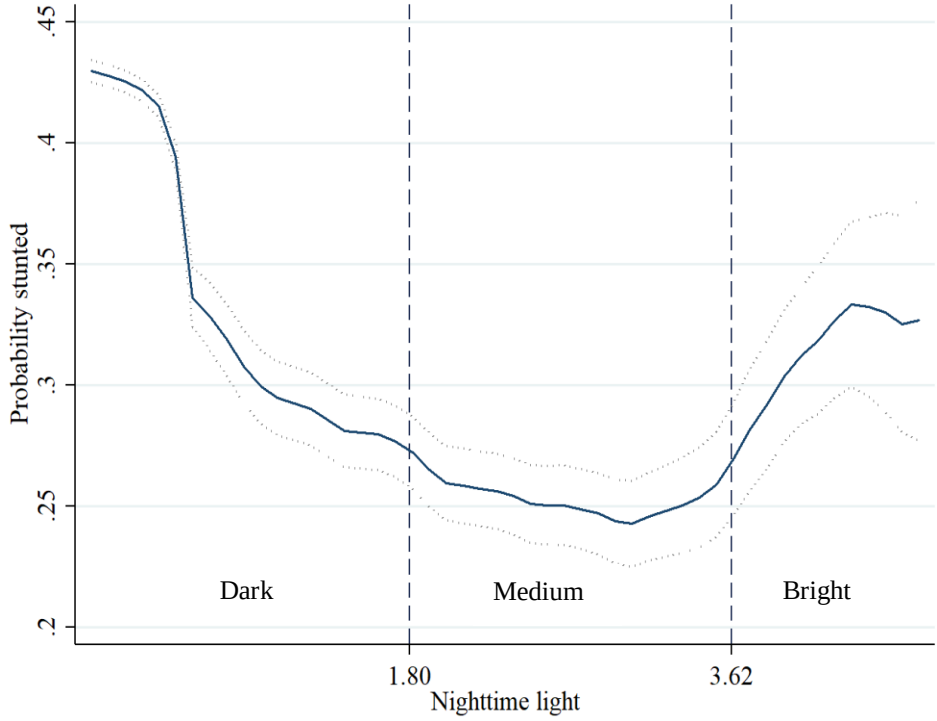
Source: NOAA nighttime light observations for East Africa.
Note: Nighttime light brightness is maximized to show contrast between rural and urban regions in East Africa.

Figure 2 | Nighttime light distribution for 10 most populous cities



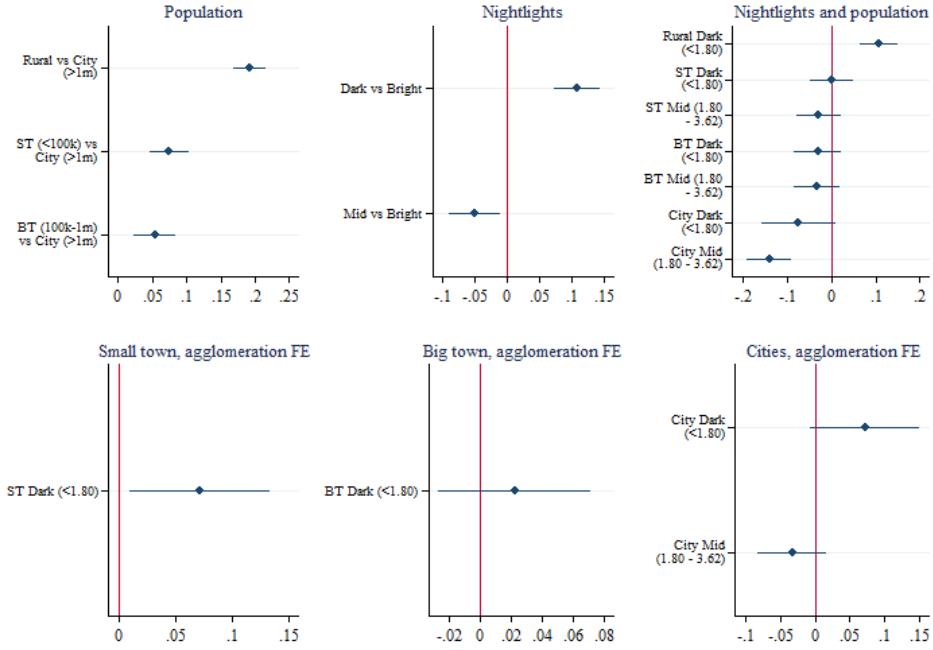
Source: 2015 DHS geophysical data for Burundi, Kenya, Ethiopia, Malawi, Mozambique, Rwanda, Tanzania, Uganda, Zambia and Zimbabwe. Africapolis (2018) population data. *N*=40,324

Figure 3 | Polynomial association between the probability a child is stunted and nighttime lights



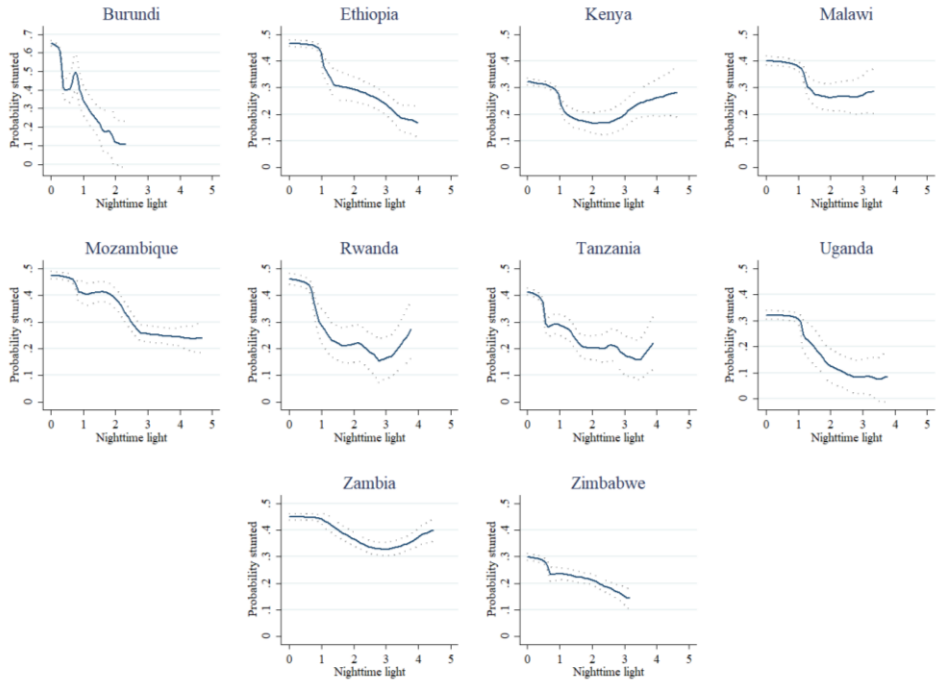
Source: 2015 DHS data for Burundi, Kenya, Ethiopia, Malawi, Mozambique, Rwanda, Tanzania, Uganda, Zambia and Zimbabwe.
Note: The nonparametric regressions are estimated through an Epanechnikov kernel function using a rule-of-thumb bandwidth estimator. The dotted lines around the plot represent the 90% confidence interval. The y-axes do not start at zero for better rendition of the graph. *N*=40,324

Figure 4 | Probability a child is stunted across population and nightlight categories



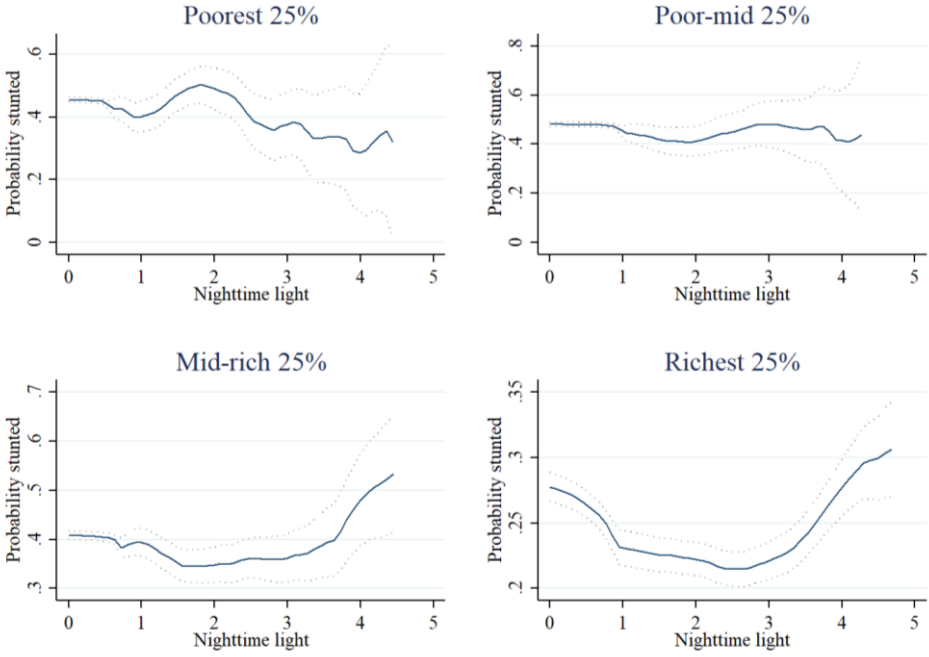
Source: 2015 DHS data for Burundi, Kenya, Ethiopia, Malawi, Mozambique, Rwanda, Tanzania, Uganda, Zambia and Zimbabwe.
Note: Coefficients and 95% confidence intervals of probability child not stunted regressed on population and nightlight category dummies. 'City (> 1m)' is the omitted category in panel 1. 'City bright (>3.62)' is the omitted category in panel 2. 'Bright (>3.62)' is the omitted category in panel 3. ST is small towns. BT is big towns. 'Small towns mid (1.80 – 3.62) is omitted in panel 4, 'Big towns mid (1.80 – 3.62) is omitted in panel 5 and 'City bright (>3.62)' is omitted in panel 5. Panel 4, 5 and 6 includes agglomeration fixed effects. *N*=40,324

Figure 5 | Probability a child is stunted, per country



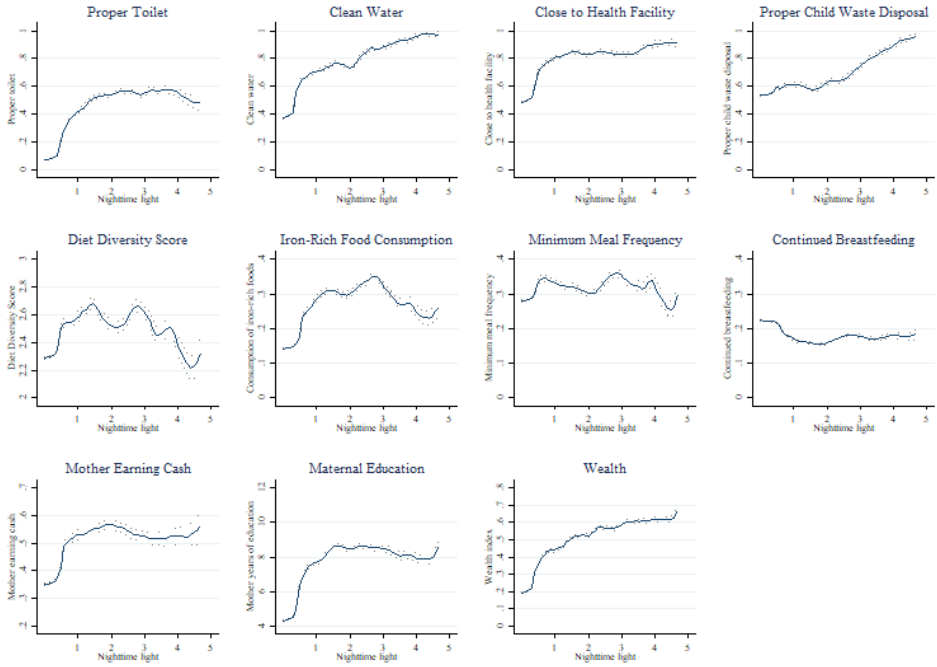
Source: 2015 DHS data for Burundi, Kenya, Ethiopia, Malawi, Mozambique, Rwanda, Tanzania, Uganda, Zambia and Zimbabwe.
Note: The nonparametric regressions are estimated through an Epanechnikov kernel function using a rule-of-thumb bandwidth estimator. The dotted lines around the plot represent the 90% confidence interval. The y-axes do not start at zero for better rendition of the graph. *N*=40,324

Figure 6 | Probability a child is stunted, per wealth category



Source: 2015 DHS data for Burundi, Kenya, Ethiopia, Malawi, Mozambique, Rwanda, Tanzania, Uganda, Zambia and Zimbabwe.
Note: The nonparametric regressions are estimated through an Epanechnikov kernel function using a rule-of-thumb bandwidth estimator. The dotted lines around the plot represent the 90% confidence interval. The y-axes do not start at zero for better rendition of the graph. *N*=40,324

Figure 7 | Urbanization and determinants of child stunting



Source: 2015 DHS data for Burundi, Ethiopia, Kenya, Malawi, Mozambique, Rwanda, Tanzania, Uganda, Zambia and Zimbabwe.
Note: The nonparametric regressions are estimated through an Epanechnikov kernel function using a rule-of-thumb bandwidth estimator. The dotted lines around the plot represent the 90% confidence interval. The y-axes do not start at zero for better rendition of the graph. *N*=40,324

2.9 Tables

Table 1 | Key statistics per population category and nightlight category

	Average population	1st percentile nightlight value	Average nightlight	99th percentile nightlight value	% children stunted
Panel A:					
Rural		0	0.06	1.80	43.29
Small town (<100k)	44767	0	0.87	3.10	31.81
Big town (100k – 1m)	343277	0	1.80	3.62	29.12
City (>1m)	2937511	0.30	3.11	4.52	23.10
Panel B:					
Dark (0 – 1.80)	245927	0	0.15	1.80	41.34
Medium (1.80 – 3.62)	1127323	1.82	2.61	3.62	25.46
Bright (>3.62)	2837623	3.63	4.07	4.68	30.58

Table 2 | Key statistics per combined population and nightlight category

Urban classification	Nightlight classification	Average nightlight (s.d.)	N	% obs.	% children stunted
Rural	Dark	0.06 (0.25)	29750	73.78	43.29
Small town	Dark	0.78 (0.57)	3612	8.96	32.2
	Medium	1.05 (1.14)	1927	4.78	31.09
Big town	Dark	0.78 (0.60)	1332	3.3	28.53
	Medium	2.61 (0.50)	1651	4.09	29.56
City	Dark	1.13 (0.49)	196	0.49	25.51
	Medium	2.89 (0.47)	1184	2.94	18.58
	Bright	4.08 (0.26)	672	1.67	30.36
Total			40324	100	

Table 3 | Regression results for child stunting and nighttime lights

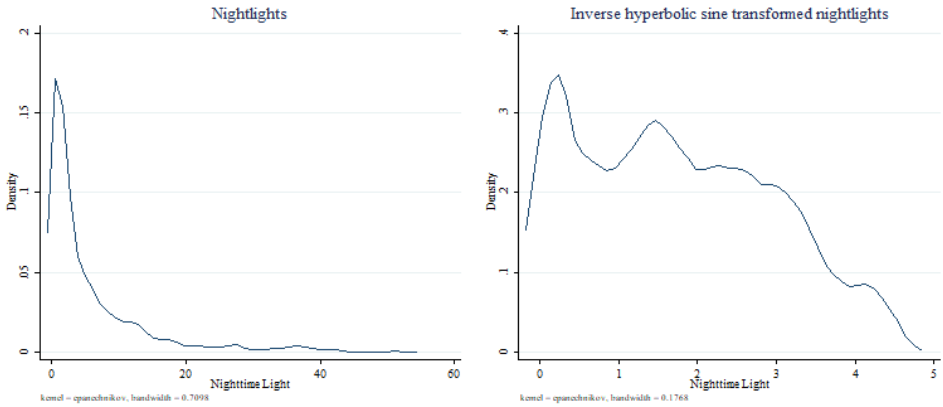
VARIABLES	(1) Nighttime lights	(2) Controls	(3) Health Inputs	(4) Feeding practices	(5) Maternal characteristics	(6) Wealth	(7) All variables
Panel A:							
Dark (0 - 1.80) vs NL > 1.80	0.161***	0.147***	0.0797***	0.135***	0.0902***	0.0113	0.00164
	(0.00896)	(0.00881)	(0.0101)	(0.00904)	(0.00929)	(0.0107)	(0.0108)
R-squared	0.011	0.064	0.070	0.065	0.078	0.079	0.086
Panel B:							
Dark (0 - 1.80) vs Bright (> 3.62)	0.0876***	0.0931***	0.0214	0.0848***	0.0378*	-0.0634***	-0.0684***
	(0.0214)	(0.0212)	(0.0219)	(0.0214)	(0.0212)	(0.0223)	(0.0223)
Medium (1.80 - 3.62) vs Bright (> 3.62)	-0.0945***	-0.0687***	-0.0738***	-0.0636***	-0.0667***	-0.0929***	-0.0873***
	(0.0230)	(0.0227)	(0.0228)	(0.0228)	(0.0224)	(0.0226)	(0.0225)
R-squared	0.012	0.064	0.071	0.066	0.078	0.080	0.087
Controls							
Basic controls		x	x	x	x	x	x
Health inputs			x				x
Feeding practices				x			x
Maternal characteristics					x		x
Wealth						x	x

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Note: Linear probability model explaining child stunting and urbanization. Basic controls include mother's age, whether household head is male, household size and a full set of dummies for gender, age (in months) and country. Healthcare access and sanitation includes four dummies on whether the household has an accessible health facility, a proper toilet (defined by having a flushing system or ventilated improved latrine), clean water (defined by piped into the dwelling or plot, coming from a public tap or tube well, a tanker truck or bottled water), disposes of child waste properly (defined by flushing waste down a toilet or latrine or thrown into the garbage). Feeding practices are based on cluster levels averages. They include a diet diversity score (1-7), iron-rich food consumption, minimum meal frequency and continued breastfeeding after 12 months of age. Maternal characteristics include a dummy on mother earning in cash and years of formal education of the mother. Wealth is represented by a wealth index calculated by a multiple correspondence analysis using household assets (electricity, radio, television, refrigerator, bicycle, motorcycle, car/truck, tile/concrete floor, metal roof, cement walls and non-wood cooking fuel). N=40,324.

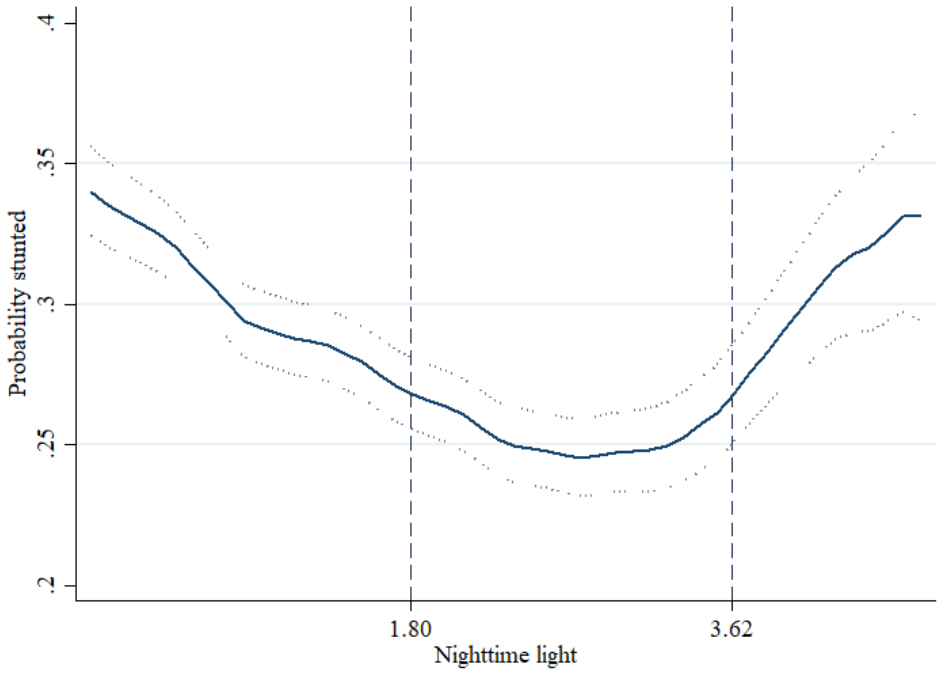
2.10 Appendix

Figure A1 | Distribution of raw nightlight data and inverse hyperbolic sine nightlights for Africapolis urban households in our sample



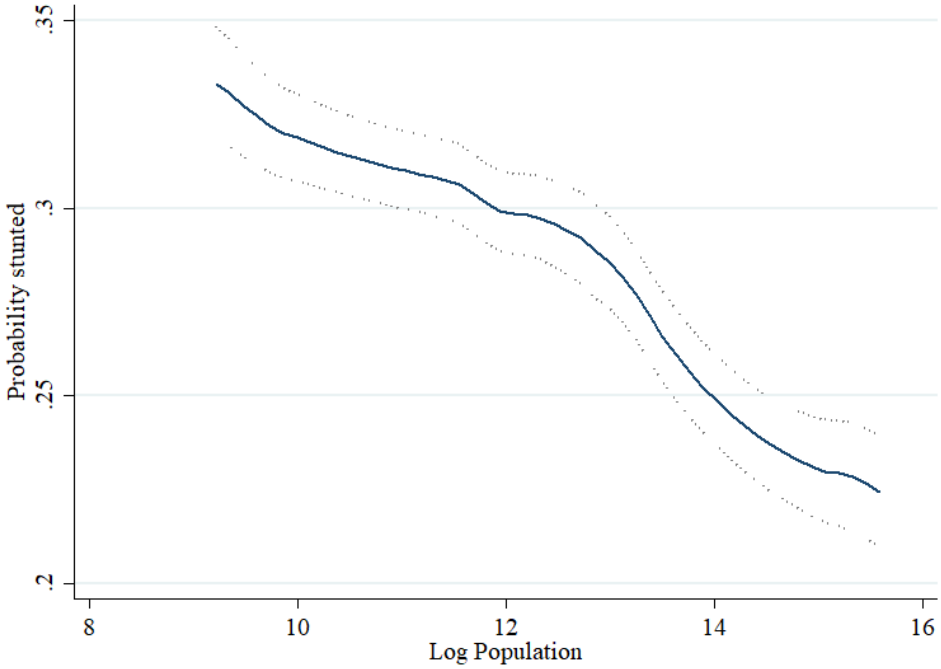
Source: 2015 DHS geophysical data for Burundi, Kenya, Ethiopia, Malawi, Mozambique, Rwanda, Tanzania, Uganda, Zambia and Zimbabwe.
Note: 11,566 urban observations as defined by children living in regions included in the Africapolis dataset

Figure A2 | Probability a child is stunted and nighttime lights, for Africapolis urban sample only



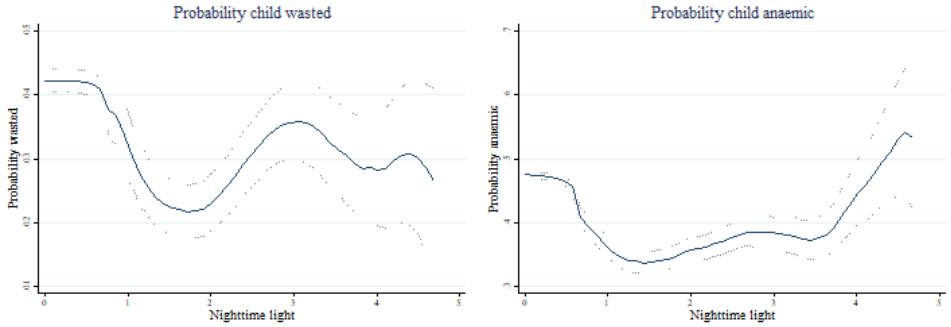
Source: 2015 DHS data for Burundi, Kenya, Ethiopia, Malawi, Mozambique, Rwanda, Tanzania, Uganda, Zambia and Zimbabwe.
Note: The nonparametric regressions are estimated through an Epanechnikov kernel function using a rule-of-thumb bandwidth estimator. The dotted lines around the plot represent the 90% confidence interval. The y-axes do not start at zero for better rendition of the graph. *N*=40,324

Figure A3 | Probability a child is stunted and log population



Source: 2015 DHS data for Burundi, Kenya, Ethiopia, Malawi, Mozambique, Rwanda, Tanzania, Uganda, Zambia and Zimbabwe.
Note: The nonparametric regressions are estimated through an Epanechnikov kernel function using a rule-of-thumb bandwidth estimator. The dotted lines around the plot represent the 90% confidence interval. The y-axes do not start at zero for better rendition of the graph. *N*=40,324

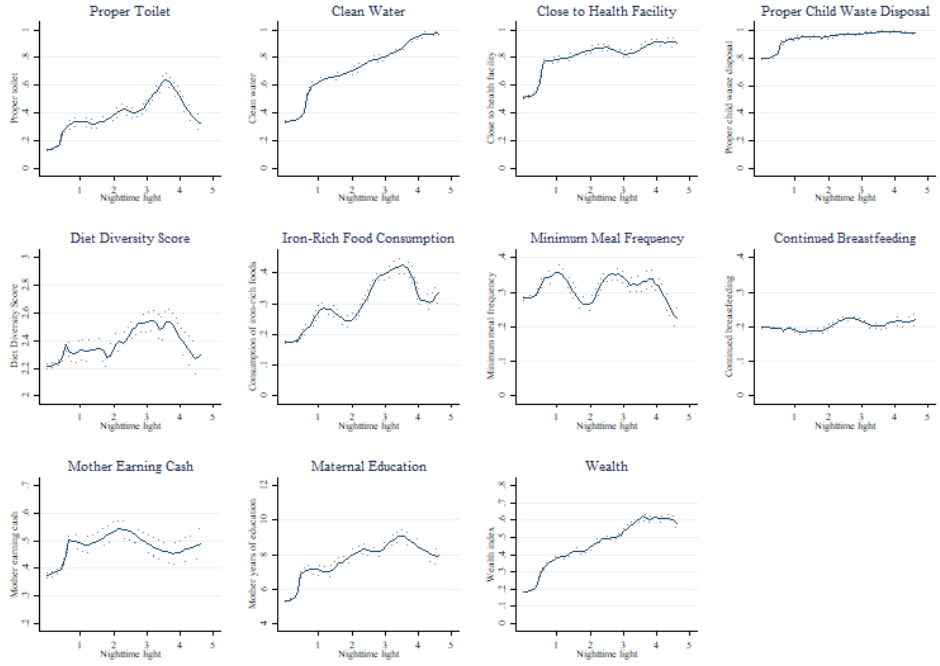
Figure A4 | Child wasting and anaemia levels



Source: 2015 DHS data for Burundi, Kenya, Ethiopia, Malawi, Mozambique, Rwanda, Tanzania, Uganda, Zambia and Zimbabwe.

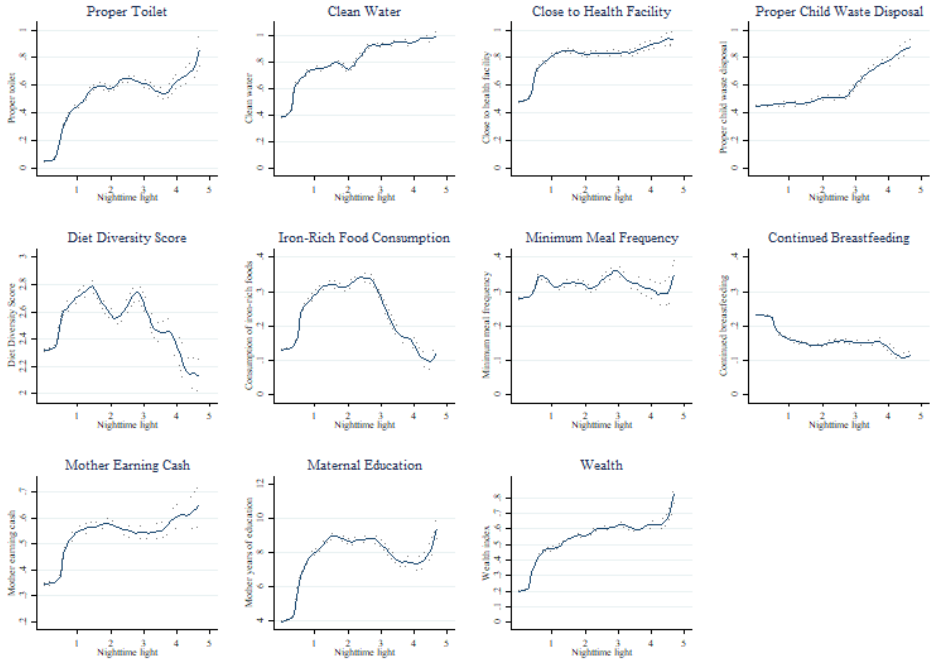
Note: The nonparametric regressions are estimated through an Epanechnikov kernel function using a rule-of-thumb bandwidth estimator. The dotted lines around the plot represent the 90% confidence interval. The y-axes do not start at zero for better rendition of the graph. *N*=40,324

Figure A5 | Urbanization and determinants of child stunting, Kenya and Zambia



Source: 2015 DHS data for Burundi, Kenya, Ethiopia, Malawi, Mozambique, Rwanda, Tanzania, Uganda, Zambia and Zimbabwe.
Note: The nonparametric regressions are estimated through an Epanechnikov kernel function using a rule-of-thumb bandwidth estimator. The dotted lines around the plot represent the 90% confidence interval. The y-axes do not start at zero for better rendition of the graph. *N*=40,324

Figure A6 | Urbanization and determinants of child stunting, other countries



Source: 2015 DHS data for Burundi, Kenya, Ethiopia, Malawi, Mozambique, Rwanda, Tanzania, Uganda, Zambia and Zimbabwe.
Note: The nonparametric regressions are estimated through an Epanechnikov kernel function using a rule-of-thumb bandwidth estimator. The dotted lines around the plot represent the 90% confidence interval. The y-axes do not start at zero for better rendition of the graph.
N=40,324

Table A1 | Regression results for child stunting and nighttime lights, per country

VARIABLES	(1) Total	(2) Burundi	(3) Ethiopia	(4) Kenya	(5) Malawi	(6) Mozambique	(7) Rwanda	(8) Tanzania	(9) Uganda	(10) Zambia	(11) Zimbabwe
Panel A:											
Dark (0 - 1.80) vs NL > 1.80	-0.161***	-0.506***	-0.250***	-0.108***	-0.188***	-0.192***	-0.265***	-0.214***	-0.205***	-0.0873***	-0.109***
	(0.00896)	(0.0960)	(0.0343)	(0.0296)	(0.0450)	(0.0200)	(0.0356)	(0.0283)	(0.0566)	(0.0177)	(0.0175)
Observations	40,324	3,250	4,692	4,429	2,523	4,969	1,828	4,641	2,096	6,492	5,404
R-squared	0.011	0.006	0.007	0.007	0.012	0.019	0.017	0.017	0.007	0.006	0.008
Panel B:											
Dark (NL 0 - 1.80) vs Bright (> 3.62)	0.0662***	0.506***	0.286***	0.0713*	0.170***	0.278***	0.233***	0.249***	0.248***	0.0438	0.125***
	(0.0229)	(0.0960)	(0.0361)	(0.0409)	(0.0553)	(0.0291)	(0.0660)	(0.0345)	(0.0489)	(0.0291)	(0.0223)
Medium Dark (NL 1.80 - 2.40) vs Bright (> 3.62)	-0.111***		0.0731	-0.152***	-0.0654	0.205***	-0.0250	0.0818	0.0553	-0.0998**	0.0387
	(0.0268)		(0.0835)	(0.0525)	(0.0859)	(0.0501)	(0.0829)	(0.0550)	(0.104)	(0.0402)	(0.0317)
Medium (NL 2.40 - 3.01) vs Bright (> 3.62)	-0.136***		0.0788	-0.0588		0.0589	-0.0696		0.0736	-0.0537	
	(0.0264)		(0.0852)	(0.0648)		(0.0470)	(0.0870)		(0.136)	(0.0414)	
Medium Bright (NL 3.01 - 3.62) vs Bright (> 3.62)	-0.0923***					0.0516				-0.0756*	
	(0.0294)					(0.0377)				(0.0429)	
Observations	40,324	3,250	4,692	4,429	2,523	4,969	1,828	4,641	2,096	6,492	5,404
R-squared	0.013	0.006	0.007	0.010	0.012	0.022	0.017	0.017	0.007	0.008	0.008

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A2 | Regression results for child stunting and nighttime lights, other countries

VARIABLES	(1) Nighttime lights	(2) Controls	(3) Healthcare access and sanitation	(4) Feeding practices	(5) Maternal characteristics	(6) Wealth	(7) All variables
Panel A:							
Dark (0 - 1.80) vs NL > 1.80	0.216***	0.185***	0.103***	0.168***	0.118***	0.0386***	0.0259**
	(0.0105)	(0.0105)	(0.0122)	(0.0108)	(0.0111)	(0.0127)	(0.0129)
R-squared	0.015	0.069	0.078	0.072	0.086	0.087	0.095
Panel B:							
Dark (0 - 1.80) vs Bright (> 3.62)	0.220***	0.257***	0.152***	0.244***	0.172***	0.0701**	0.0526*
	(0.0278)	(0.0279)	(0.0288)	(0.0281)	(0.0275)	(0.0286)	(0.0285)
Medium (1.80 - 3.62) vs Bright (> 3.62)	0.00460	0.0785***	0.0534*	0.0829***	0.0576**	0.0338	0.0286
	(0.0294)	(0.0294)	(0.0293)	(0.0296)	(0.0285)	(0.0287)	(0.0285)
R-squared	0.015	0.070	0.078	0.072	0.086	0.087	0.095
Controls							
Basic controls		x	x	x	x	x	x
Healthcare access and sanitation			x				x
Feeding practices				x			x
Maternal characteristics					x		x
Wealth						x	x

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Every regression contains 29,403 observations.

Table A3 | Regression results for child stunting and nighttime lights, Zambia and Kenya only

VARIABLES	(1) Nighttime lights	(2) Controls	(3) Healthcare access and sanitation	(4) Feeding practices	(5) Maternal characteristics	(6) Wealth	(7) All variables
Panel A:							
Dark (0 - 1.80) vs NL > 1.80	0.0695***	0.0974***	0.0479***	0.0897***	0.0591***	-0.0120	-0.0223
	(0.0153)	(0.0150)	(0.0171)	(0.0154)	(0.0158)	(0.0189)	(0.0191)
R-squared	0.004	0.048	0.052	0.049	0.058	0.059	0.065
Panel B:							
Dark (0 - 1.80) vs Bright (> 3.62)	0.0202	0.0485*	-0.00642	0.0418	0.0125	-0.0764***	-0.0870***
	(0.0259)	(0.0254)	(0.0269)	(0.0256)	(0.0256)	(0.0286)	(0.0288)
Medium (1.80 - 3.62) vs Bright (> 3.62)	-0.0820***	-0.0811***	-0.0880***	-0.0800***	-0.0777***	-0.100***	-0.100***
	(0.0300)	(0.0292)	(0.0292)	(0.0293)	(0.0289)	(0.0292)	(0.0292)
R-squared	0.005	0.049	0.054	0.051	0.059	0.062	0.067
Controls							
Basic controls		x	x	x	x	x	x
Healthcare access and sanitation			x				x
Feeding practices				x			x
Maternal characteristics					x		x
Wealth						x	x

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Every regression contains 10,921 observations.

Table A4 | Regression results for child stunting and nighttime lights, per wealth category

VARIABLES	(1) Nighttime lights	(2) Controls	(3) Health Inputs	(4) Feeding practices	(5) Maternal character-istics	(7) All varia-bles
Panel A: Poorest 25%						
Dark (0 - 1.80) vs Bright (> 3.62)	0.122	0.115	0.112	0.107	0.0848	0.0759
	(0.134)	(0.131)	(0.130)	(0.133)	(0.135)	(0.137)
Medium (1.80 - 3.62) vs Bright (> 3.62)	0.119	0.108	0.113	0.107	0.108	0.110
	(0.143)	(0.139)	(0.138)	(0.141)	(0.143)	(0.145)
Observations	12,179	12,179	12,179	12,179	12,179	12,179
R-squared	0.055	0.057	0.058	0.059	0.061	0.063
Panel B: Poor-mid 25%						
Dark (0 - 1.80) vs Bright (> 3.62)	-0.0117	-0.0120	-0.0390	-0.0147	-0.0224	-0.0469
	(0.220)	(0.220)	(0.222)	(0.231)	(0.206)	(0.219)
Medium (1.80 - 3.62) vs Bright (> 3.62)	-0.0281	-0.0304	-0.0461	-0.0308	-0.0288	-0.0435
	(0.227)	(0.227)	(0.228)	(0.237)	(0.213)	(0.225)
Observations	8,425	8,425	8,425	8,425	8,425	8,425
R-squared	0.055	0.055	0.056	0.058	0.058	0.062
Panel C: Mid-rich 25%						
Dark (0 - 1.80) vs Bright (> 3.62)	-0.0737	-0.0793	-0.111	-0.0804	-0.0600	-0.0869
	(0.0722)	(0.0724)	(0.0741)	(0.0726)	(0.0711)	(0.0727)
Medium (1.80 - 3.62) vs Bright (> 3.62)	-0.130*	-0.133*	-0.141*	-0.128*	-0.107	-0.111
	(0.0765)	(0.0766)	(0.0779)	(0.0769)	(0.0753)	(0.0765)
Observations	9,741	9,741	9,741	9,741	9,741	9,741
R-squared	0.061	0.062	0.065	0.063	0.069	0.073
Panel D: Richest 25%						
Dark (0 - 1.80) vs Bright (> 3.62)	0.00541	0.00386	-0.0296	0.00432	-0.0101	-0.0293
	(0.0237)	(0.0237)	(0.0244)	(0.0238)	(0.0236)	(0.0243)
Medium (1.80 - 3.62) vs Bright (> 3.62)	-0.077***	-0.077***	-0.080***	-0.075***	-0.072***	-0.078***
	(0.0242)	(0.0241)	(0.0242)	(0.0242)	(0.0239)	(0.0241)
Observations	9,979	9,979	9,979	9,979	9,979	9,979
R-squared	0.052	0.056	0.062	0.057	0.071	0.074
Controls						
Basic controls		x	x	x	x	x
Healthcare access and sanitation			x			x
Feeding practices				x		x
Maternal characteristics					x	x
Wealth						x

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Chapter 3. Dietary quality in rural and urban Tanzania*

3.1 Introduction

Hunger and malnutrition remain prominent issues in sub-Saharan Africa. In 2018, 237 million people were undernourished in this region, a rise of about 33 million compared to 2015 (FAO & ECA, 2018). At the same time, urbanization rates are soaring, with an annual urban population growth of around 4% compared to the world average of 2% (United Nations, 2019). The United Republic of Tanzania hosts an interesting intersection between these two phenomenon, with a relatively high undernourishment rate of 32% (FAO & ECA, 2018), and about 35% of the population living in urban areas, most highly concentrated in Dar es Salaam (United Nations, 2019).

Urban diets tend to be more diversified, with traditional diets rich in grains, roots and tubers, and local vegetables being supplemented with imported foods (Sodjinou et al., 2009). Urban residents tend to consume higher amounts of meat, dairy products, fruits and vegetables (Chernichovsky & Meesook, 1984; Huang & Bouis, 2004; Worku et al., 2017). However, studies warn that urbanization may lead to overconsumption (Popkin et al., 2012). More precisely, the nutrition transition argues that urban areas in lower income countries have shifted towards more energy intensive diets, dominated by processed 'fast-food' and higher oil and sugar intakes (Popkin, 1999; 2004; Worku et al., 2017). Moreover, a growing dependence on street foods is present in urban areas (Maxwell et al., 2000; Maruapula et al., 2011). In Dar es Salaam, street foods account for almost three-quarters of the total calorie consumption of the urban poor and middle-income groups (Kinabo, 2004). Combined with a more sedentary lifestyle, these shifts can lead to health issues such as obesity and other nutrition related non-communicable diseases (Popkin, 1999; 2004; Popkin et al., 2012). The triple burden of malnutrition accentuates how in many developing countries undernourishment and micronutrient deficiencies are prevailing at the same time as rising obesity rates (IFPRI, 2016; Ameye & Swinnen, 2019).

* This is a single-authored paper.

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The literature assessing rural-urban dietary disparities faces several shortcomings. First, despite the growing consensus on the crucial importance of nutrition for long-term health (Black et al., 2008; Bhutta et al., 2008), the majority of the literature continues to focus on quantity rather than quality of food consumption. Even within the literature focusing on dietary quality, there are various limitations. Dietary patterns are often established using clustering methods, where several food items are grouped together (e.g. Crozier et al., 2006; Sodjinou et al., 2009). These are dependent on subjective decision-making, such as grouping and labelling clusters, are unstable across time, and due to naming and number differences, are incomparable across studies (Martikainen et al., 2003). Aggregate measures such as diet diversity[25] and nutrient adequacy scores are also commonly used, however these scores lack the ability to identify where the problem of malnutrition lies. Dietary quality assessed through the Diet Quality Index-International (DQI-I) also lacks information. Kim et al. (2003) find that the DQI-I scores for China and the US are fairly similar, but these need to be broken down to assess which countries fare better in certain subcategories, as both countries still experience considerable micronutrient deficiencies. Second, within this literature urbanization is generally regarded as a binary concept, placing households in either rural or urban areas. Any distinctions between urban areas are therefore disregarded. However, these distinctions can identify important differences in food consumption and health questions (Cockx et al., 2018; Amare et al., 2020; Ameye & De Weerdt, 2020).

In order to clarify rural-urban food consumption disparities in Tanzania, we will assess the dietary composition of rural households, those living in smaller towns and cities (henceforth referred to as secondary towns), and those living in Dar es Salaam. By dissecting highly detailed food consumption diaries from the 2007-2008 Survey of Household Welfare and Labour in Tanzania, we identify a two-week diet for 1,506 households in Tanzania. From these data we calculate the percentage consumed relative to dietary reference intakes of calories, protein, fats, sugars, fiber and 16 micronutrients, taking into account the age and gender composition of each household.

A handful of studies use micronutrient decompositions to differentiate between rural and urban diets in sub-Saharan Africa. Our paper expands on this work in four ways. First, we use a dataset from 2007-2008, a period slightly after the 2002 take-off in Tanzania's urbanization (United Nations, 2019). This much better reflects rural-urban differences compared to studies focusing on

[25] Note there are several ways to measure diet diversity. The WHO (2008) recommends a 7-food group indicator for children 6-24 months of age. FAO and USAID's Food and Nutrition Technical Assistance III Project (FANTA) proposes a 10-food group indicator to assess women's dietary diversity (FAO & FHI360, 2016) and a 12-food group indicator for household level analysis (Swindale & Bilinsky, 2006).

earlier time periods (e.g. Mazengo et al.,1997; MacIntyre et al., 2002; Bourne et al., 2002). Second, we capture various urban locations from five regions across the country and differentiate between small towns and cities, and Dar es Salaam. Being the country's commercial capital, studies focusing solely on Dar es Salaam (Mazengo et al., 1997; Abdulai & Aubert, 2004) are prone to missing important information. Third, we use detailed food diaries covering a two-week period to determine nutrient consumption. This method ensures a thorough representation of the average daily diet, unlike shorter time periods which provide insufficient evidence on the prevalence and depth of malnourishment (Fiedler, 2013). A 24-hour timespan, for example, excludes certain foods that may only be consumed a few times a week. Thorough diary methods may also be preferable to recall surveys as they are less subject to reporting errors and telescoping (De Weerdt et al., 2016). Fourth, we have a larger sample size than most studies enabling less location and time specific results.

Our findings highlight a substantial difference in dietary composition between rural areas, secondary towns and Dar es Salaam. Households living in secondary towns tend to consume more than rural households in terms of macro- and micronutrients, and so are less likely to face issues of hunger and micronutrient deficiencies. However, dietary patterns in Dar es Salaam are less promising, with a higher consumption of fats and sugar, but a lower consumption of protein, fiber and several key vitamins (thiamine, niacin, folate and vitamin C and E) and minerals (calcium and potassium).

We then try to assess the drivers behind these dietary differences. First, urbanization and income are highly correlated. Additional income can ensure higher diet diversity and improvements in the quality of food bought (Regmi & Meade, 2013), but may also lead to higher opportunity costs for working parents. This is further related to differences in rural and urban lifestyles and demand for convenience (e.g. if more women work outside of the household). Second, educational attainments are also higher in urban regions. Education can influence both future income and knowledge on nutrition. Third, food systems are different in urban areas with modern retailers (such as supermarkets) playing a larger role (Reardon et al., 2003; Demmler et al., 2018). Supermarkets may provide cheaper foods, as well as dairy and meat, but also stimulate the consumption of highly processed foods (Qaim, 2017; Khonje et al., 2020). Urban clusters may also provide better food accessibility and economies of scale. Fourth, food prices further influence household consumption decisions (Alem & Söderbom, 2012; Masters et al., 2018) and can be highly differential between rural and urban areas (Garrett & Ruel, 1999; Majumder et al., 2012).

When controlling for possible mechanisms, we find that education, wealth and food prices have a significant impact on our results. The fat, saturated fat

and sugar consumption differentials between rural areas, secondary towns and Dar es Salaam are smaller when controlling for these drivers. Differences in vitamin and mineral consumption are also partly explained for secondary towns, but significant differences remain between rural consumption and that in Dar es Salaam, especially in terms of micronutrients.

Section 3.2 of this paper will describe our data, section 3.3 presents the regression analysis and section 3.4 the results. Section 3.5 presents our conclusions.

3.2 Data

Throughout the literature most datasets provide aggregate information on food consumption, but this lacks the necessary level of detail to investigate dietary quality. In order to provide a more elaborate overview of nutrient deficiencies in rural and urban areas, we use the Survey of Household Welfare and Labour in Tanzania 2007-2008 (SHWALITA). The data covers five regions in Tanzania: Dodoma, Pwani, Dar es Salaam (DSM), Shinyanga and Kagera. These locations were purposely selected to capture variations in socio-economic and geographic climate between different rural and urban locations (Beegle et al., 2012). Dar es Salaam and Pwani border the Indian ocean on the East, Dodoma is found at the centre of the country, Kagera borders Uganda, Rwanda, Burundi and Lake Victoria on the North-west side, and Shinyanga is situated between the Kigosi and Maswa game reserves in the North. From these regions, communities were randomly selected from the 2002 Census, from which a random sub-village was chosen and a random selection of households. Table 1 presents the rural-urban distribution of households across the regions in our sample. Dar es Salaam and Dodoma are largely urban regions, which is represented by the majority of surveyed households coming from urban areas within these regions. Conversely, Kagera, Shinyanga and Pwani are represented by a higher number of rural households.

Previous studies largely focus on a rural-urban binary, however, there may be large disparities in food consumption between various types of urban areas. In order to assess this, we will disaggregate our urban category into two groups: secondary towns and Dar es Salaam. After DSM, Arusha and Mwanza are the two largest cities in Tanzania, but these are not sampled in our study. Therefore, DSM represents the largest city, an example of the highest levels of urbanization with a population of about 5.3 million, and secondary towns represent smaller cities and towns. The largest cities in this category are Dodoma, the

legislative capital with a population around 270,000, as well as Bukoba in Kagera, Shinyanga city in Shinyanga and Bagamoyo in Pwani, each with a population between 47,000 and 170,000 (SWAC/OECD Africapolis, 2018).[26]

3.2.1. Sample characteristics

Table 2 presents an overview of the types of households living in rural areas, secondary towns and DSM in our sample. We observe a significant difference between all three groups, indicating the importance of making distinctions between urban areas. First, households living in secondary towns are more likely to have a female household head, at 23%, compared to 20% in rural areas and 16% in DSM. Rural and secondary town household heads have a similar age and educational level, while those in Dar es Salaam are about 5 years younger and have about 2 years more education. Household size is smaller in secondary towns and in DSM than in rural areas, where there are more children below the age of 15.

The percentage of married household heads is 6% points higher in secondary towns than in rural areas, and again 7% points higher in DSM. Conversely, polygamous relationships are much more common in rural than in urban areas. The normalized asset index[27] indicates that households in secondary towns are almost twice as wealthy as those in rural areas. Households in DSM are more than three times as wealthy. Nevertheless, rural households own more acres of land, synonymous with a more agriculturally based society compared to that in a city.

3.2.2. Food consumption

In order to establish the food consumption patterns of rural, secondary town and DSM households, we will use the SHWALITA household and personal diary modules as they provide the level of detail required for our analysis. The diaries specify a rich description of what households ate during the two weeks of surveying. These modules are of an acquisition type, adding all products coming into the household through harvests, purchases, gifts and stock reductions, and subtracting all items not consumed by the household through sales, stock increases and gifts. Meals going to guests and food consumed outside of the household are also recorded in the diaries. In order to avoid unit conversion errors, households completed the food consumption diaries in local units,

[26] 988 households live in rural areas, 304 in secondary towns and 214 in Dar es Salaam. Results for Dodoma are in line with those for secondary towns, therefore these are grouped together into one category.

[27] The asset index includes whether the household owns a bicycle, a mobile, has a good floor and electricity.

which are then converted into standard measures using item and region-specific food composition tables. These tables also take edible portions of the food consumed into account[28].

The original SHWALITA diaries are recorded on the basis of 58 food items and groups.[29] However, households also document the Swahili names for the specific foods consumed. After translation and following disaggregation of grouped foods[30], our final dataset now contains 99 different food items (refer to Table A1). These disaggregations represent significant differences. Originally, full meals and different types of snacks were grouped together, but rural areas tend to consume more nutritional rice meals, containing higher levels of vitamins and minerals, and urban dwellers tend to consume more calorie-dense oily porridges and street foods. Moreover, the nutritional content of snacks varies vastly, with a meat skewer equating to around 450 kcal but a roasted banana amounting to 120 kcal. In terms of sugar, fat and fiber content, consuming a chapatti or samosa also differs greatly from a donut or cake. An extra advantage of these disaggregations is that additional ingredients can now be taken into account. For example, we include methods of preparation and oils used in full meals, giving a more accurate description of exact consumption.[31]

To aid interpretation, our analysis will use the average adult equivalent household nutrient consumption relative to dietary reference intakes.[32] Daily recommended calorie calculations follow Smith et al. (2006) dependent on age, sex and breastfeeding status. Dietary reference intakes for macronutrients, vitamins and minerals are derived from Meyers et al. (2006)[33], including maximum values to ensure consumption remains under toxicity levels (in the case of some

[28] For example, a bunch of plantains carry a considerable amount of non-edible material and so this is acknowledged and subtracted in the conversion tables.

[29] Previous literature often simplifies food groups even further into representative groups such as cereals, roots and tubers, fruit, vegetables, meat and dairy products.

[30] For example, we establish whether items from food group "tomatoes, onions, carrots" are a tomato, onion or carrot and so these three items are disaggregated into three separate groups.

[31] Nutrient specific information collected from Tanzania food composition tables by Lukmanji, Z., Hertzmark, E., Mlingi, N., Assey, V., Ndossi, G., & Fawzi, W. (2008).. *MUHAS-TFNC, HSPH, Dar es Salaam Tanzania.*

[32] As our diaries are of an acquisition type our data does not include information on the food consumed by each member of the household. Intra-household distributions can therefore not be assessed.

[33] Dietary reference intakes (DRI) include 4 subsets of recommendations. We use the recommended dietary allowance (RDA), determining the average daily dietary nutrient intake level that is sufficient to meet the nutrient requirements of nearly all (97–98 percent) healthy individuals in a particular life stage and gender group, and the tolerable upper intake level, the highest average daily nutrient intake level that likely poses no adverse health risks to almost all individuals in the general population (Meyers et al., 2006).

vitamins and minerals).[34] We present information on calories, protein, animal protein, fat, saturated fat, cholesterol, carbohydrates, fiber, sugar, vitamins (A, B1, B2, B3, B6, B9, B12, C, E) and minerals (calcium, phosphorus, iron, sodium, magnesium, zinc and potassium)[35].

Before zooming in on detailed macro- and micronutrient consumption, Table 3 presents the consumption of specific food groups in rural areas, secondary towns and Dar es Salaam. All households consume a high portion of cereals and cereal products, although secondary towns consume about 2-3% points more than rural and DSM households. Rural households primarily consume vegetables, cereals, roots and tubers, and fruit making up 18%, 16%, 14% and 10% of their diet. Households living in secondary towns mostly consume cereals at 19%, followed by vegetables (15%) and other drinks (14%). Vegetables are only the third most consumed food group for households in DSM, at 10%, compared to other drinks consumption such as juice, coffee and carbonated drinks at 18% and cereals at 17%. Households in DSM consume more highly-processed cereal products like bread and pasta, compared to rural and secondary town households (Table A1, Appendix). All regions consume quite little seafood, eggs and dairy products, ranging between 0.2 - 4%. Meat consumption is relatively similar in all regions, making up about 6% of the total diet, although urban households consume more beef and chicken, and rural households are more focused on rabbit, meat broths and soup (Table A1, appendix).

Most evident is the difference in snacks, sweets and alcoholic beverage consumption. Households in DSM consume more snacks (8%), sugars and honey (6%) and full meals bought outside of the household (6%) compared to rural areas (4%, 5%, 3%) and secondary towns (6%, 4% and 3%). Fried snacks such as samosas, fried cassava, fried beef and donuts are especially common in DSM (Table A1, appendix). Households living in secondary towns consume most alcoholic beverages, making up 8% of their diet instead of 6% in rural areas and DSM. In terms of dietary variety and how consumption is distributed amongst food groups, rural households tend to consume more vitamin and mineral rich foods and less unhealthy fast foods.

Although the dietary composition of rural households seems preferable, this does not indicate that rural households are consuming sufficient macro- and

[34] Note that the focus of this paper lies on nutritional requirements and not exact digestive nutrient intake goals. This is due to limited information on bioavailability and food processing.

[35] Nutritional information derives from the provided information given by the Tanzania Food Composition Tables, encompassing key vitamins and minerals. The chosen nutrients reflect and array of key macro- and micronutrients, as well as those commonly under consumed in SSA. To simplify, calories will be referred to as nutrients, although not technically so. Saturated fat, a subcategory of fat, and sugar and fiber, subcategories of carbohydrates, will also be referred to as macronutrients.

micronutrients or that urban households are not doing so. Therefore, Figure 1 presents macronutrient, vitamin and mineral consumption relative to the dietary reference intakes across our rural and urban categories (perfect consumption falls at zero[36]).

We find that essential macronutrient consumption (calories, fat, protein and carbohydrates) is higher in secondary towns than rural areas, but is again lower in Dar es Salaam (panel A). These average consumption levels seems positive but from Table A2 (Appendix), we find that about 48% of rural households, 27% of secondary town households and 38% of DSM households are calorie deficient. A higher consumption in secondary towns is therefore paired with less overall deficiencies. This is especially important for key nutrients such as protein, animal protein and fat. We include animal protein to highlight the importance of animal-sourced protein, containing all nine essential amino acids, compared to plant-based protein which is often deficient in one or more of these amino acids. Here we find that on average, only 45% of all protein consumption comes from animal sources in rural households, 42% in secondary towns and 40% in DSM. Table A2 also highlights that if full protein requirements were to be taken from animal-sourced foods, about 90% of households would be protein deficient in all areas. At the same time, nutrients that are potentially harmful to health when overconsumed, such as saturated fat, cholesterol and sugar, are consumed more often in Dar es Salaam.

These patterns are reflected in terms of vitamin and mineral consumption (panel B and C). In general, micronutrient consumption is better in secondary towns than in rural areas. However, vitamin and mineral consumption is again lower for households living in Dar es Salaam (except for vitamin B12 and sodium). Although this is not necessarily a problem for nutrients such as riboflavin, phosphorus and magnesium, it can be worrisome for nutrients that are generally under consumed already. Vitamin C, folate, calcium and potassium consumption is becoming extremely low, and the consumption levels of niacin, Vitamin E and iron are also worrying. From Table A2, we can observe that the highest micronutrient deficiencies are found in DSM, whereas secondary towns generally perform better.

[36] Positive values mean the average household member is consuming more than the DRI, negative values mean the average household member is consuming less than the DRI.

3.3 Regression analysis

3.3.1. Rural-urban disparities

In order to empirically test previous findings and formalize the results from Figure 1, we follow an ordinary least squares framework:

$$y_i = \alpha + \beta urban_i + \epsilon_i \quad (1)$$

where y_i represents the percentage of calories, macro- or micronutrient consumed relative to the dietary reference intakes, $Urban_i$ represents three dummy variables for households living in rural areas, secondary towns or Dar es Salaam, and ϵ_i is the error term.

We then include several household characteristics which may influence consumption decisions and vary significantly between rural areas, secondary towns and DSM (Table 2). Marital status and polygamy may affect female bargaining power (Lépine & Strobl, 2013), especially for junior wives (Gibson & Mace, 2007), and can negatively affect the nutritional status of children (Gyimah, 2009). Whether the household head is female and their age can also affect the diets of the household as a whole. Although female-headed households are typically poorer, child nutritional statuses are better than in male-headed households (Kennedy & Peters, 1992). Household size and the share of household members in various age categories are also included in the regressions. As there was a disparity in survey timing we also add a control for the month interviewed to account for any seasonal differences. We continue with the following framework:

$$y_i = \alpha + \beta urban_i + \gamma \boldsymbol{X}_i + \epsilon_i \quad (2)$$

where the vector $\boldsymbol{X}_i$ containing all household controls and the month surveyed control is added to regression equation (1).

3.3.2. Pathways

Next, the literature provides suggestions for a host of mechanisms driving the differences in food consumption between rural and urban locations. We will assess whether rural-urban food consumption disparities remain after controlling for several known mechanisms, therefore revealing where future research attention should lie.

First, urban areas are typically characterized by higher incomes and higher income opportunities (Stage et al., 2010). Additional income can ensure higher diet diversity and improvements in the quality of food bought (Regmi & Meade, 2013). However, a higher income can also increase the consumption of unhealthy foods or fast foods such as sugar, sweets, pastries, and meals and snacks

consumed away from home (Cockx et al., 2018). We predict these effects to be higher in DSM than in secondary towns as larger cities present higher income opportunities and therefore opportunity costs. In order to capture household wealth in our analysis, we include a normalized asset index in our regressions.

Second, household differentiators such as education are especially important in both child and adult nutritional outcomes (e.g. Webb & Block, 2004; Burchi, 2010; Debela et al., 2017). As seen from Table 2, educational levels are higher in secondary towns, and even more so in DSM, compared to rural areas. We therefore include household head education in our analysis.

Third, food prices influence household consumption decisions (Alem & Söderbom, 2012; Masters et al., 2018) and these may vary depending on regional price differences (Garrett & Ruel, 1999; Majumder et al., 2012). Therefore, we create a regional price index for each region included in our sample. Using data on the value of local food items we determine the minimum cost of a diet reaching all dietary reference intakes through linear programming techniques.[37] This allows us to focus solely on the regional prices of food, rather than the consumer preferences from which foods are selected. Dar es Salaam is most expensive, with the minimum cost diet at 412 TZS per person per day. This is followed by Dodoma, Shinyanga and Kagera, with minimum dietary costs at 320 TZS, 310 TZS and 258 TZS, respectively. Pwani is the cheapest region at 228 TZS per person per day.

Fourth, there is a marked difference in rural and urban food systems. Food availability and accessibility are key in determining consumer choices. We therefore include whether a shop/stall, market or restaurant is present in the cluster. These variables encompass the general consumption atmosphere within a cluster. We believe households in Dar es Salaam will be most exposed to shops and restaurant's providing quick meals, snacks and processed foods.

Our econometric analysis continues with ordinary least squares regressions of the following equational form:

$$y_i = \alpha + \beta urban_i + \gamma \boldsymbol{X}_i + \partial \boldsymbol{M}_i + \epsilon_i \quad (3)$$

where y_i represents the percentage of calories, macro- or micronutrient consumed relative to the dietary reference intakes, $Urban_i$ is the dummy variable

[37] Unfortunately the SHWALITA data does not contain a detailed price survey at a lower level of aggregation. We are not able to distinguish between rural and urban area prices. However some regions are highly rural and others highly urban so it is important to include these food prices as mechanisms.

identifying rural areas, secondary towns or Dar es Salaam, $\boldsymbol{X_i}$ is a vector containing all household controls and month surveyed controls, $\boldsymbol{M_i}$ is a vector containing possible mechanisms, and ϵ_i is the error term.[38]

3.4 Results

3.4.1. Rural-urban disparities

Table 4 presents the OLS regressions results from equation (1), analysing the differences in nutrient consumption between rural areas, secondary towns and Dar es Salaam. These results mimic the findings from Figure 1. First, households living in secondary towns and Dar es Salaam have a higher calorie consumption than rural areas, by about 24% points and 17% points, respectively. For households living in secondary towns, a higher calorie consumption is mirrored by a higher consumption of all other macronutrients, except sugar. On the other hand, households living in DSM see a disproportionately higher consumption in fat and saturated fat, as well as an indifferent protein consumption and a lower fiber consumption. These findings suggest a better dietary quality for households living in secondary towns, as the DRIs are more likely to be met, but a lower quality of diets in DSM. Although DSM households may be consuming more, and may therefore face less issues of hunger, the quality of the foods consumed are worse.

These findings are confirmed by the results for vitamin and mineral consumption. Households living in secondary towns have a higher consumption of most micronutrients, whereas households living in Dar es Salaam generally consume less vitamins, with thiamine, niacin, folate and Vitamin C and E reaching worrying levels, and minerals, with calcium and potassium largely underconsumed. Households living in the most urbanized areas are overconsuming fats, saturated fats and sugar, and under consuming key vitamins and minerals, exposing them to the risks of both overconsumption and micronutrient deficiencies.

When controlling for differences in household characteristics (regressions following equation (2)), we find that most patterns hold (Table 5). The size of the coefficients is generally lower for secondary towns, indicating more similarities in rural and secondary town food consumption when controlling for household differences. Compared to Table 4, the coefficients for Dar es Salaam present the most variation. The coefficient for protein consumption in DSM is

[38] We check the variance inflation factors for all the controls included in our regression to test for multicollinearity. All variance inflation factors are below the "rule of thumb" level of 10, with the highest one falling at 4.17.

now negative and significant, and there are larger negative coefficients for the consumption of vitamins and minerals. A small difference in dietary patterns between rural areas and secondary towns transforms into a large difference with those in Dar es Salaam.

3.4.2. Pathway results

Table 6 presents the results from equation (3), assessing whether rural, secondary town and DSM nutrient consumption differences hold when controlling for various mechanisms. Years of education of the household head impacts nutrient consumption the most, with a positive and mostly significant coefficient. Education typically increases the consumption of both macro- and micronutrients. Conversely, wealthier households have a higher consumption level of potentially unhealthy substances like saturated fat, cholesterol and carbohydrates. A higher score on the asset index also delivers mostly negative coefficients in terms of vitamins and minerals. Therefore, being wealthier does not necessarily translate into a more qualitative diet.

Although we cannot capture price variations between rural and urban areas, we find that controlling for price variations between regions is highly important. The coefficient for the price index is highly significant for all nutrients except cholesterol, vitamin E and potassium. As the price index is a composite measure, it is likely to capture a relatively lower price for some items (e.g. imported food products in urban areas) and a higher price for other food items (e.g. rurally produced food products in urban areas). Regions with a higher overall price index are typically highly urbanized. Finally, the presence of a shop or market has relatively little effect on nutrient consumption, although restaurant presence does imply a higher consumption of calories, fats and carbohydrates.

Controlling for these mechanisms has significantly altered the coefficients in our regression results. First, we find that nutrients associated with the nutrition transition such as fat, saturated fat and sugar are relatively well explained by our mechanisms in both secondary towns and Dar es Salaam. The coefficients in Table 6, panel A, are smaller than in Table 5. The consumption of more unhealthy substances in urban areas may therefore be due to a combination of wealth, education, prices and the presence of shops, markets and restaurants.

Nevertheless, the coefficients for protein, vitamins and minerals do not change much, and are even exacerbated in the case of Dar es Salaam. This means there are other mechanisms at play affecting food consumption decisions in highly urbanized areas. In future research, a more thorough investigation needs to be conducted regarding the sheer size of these urban locations

and what this entails for daily life. First, large cities deal with increases in traveling distances and so commuting times become more of a constraint (Henderson, 2002). Therefore, urban households also have less time to cook and go to markets for fresh produce (Celnik et al., 2012). Due to higher income opportunities in cities, the opportunity costs for parents working or staying at home to care for children are higher, and urban parents are less likely to have family close by to help with childcare. Conveniently consumed foods are in higher demand in urban areas where both parents mostly work away from home, and the cost of household help is greater than rural areas (Huang & David, 1993). Regarding fresh food accessibility, a more densely populated area may mean less space for fresh produce markets and an influx of supermarkets selling ready-made, highly processed meals. Supermarkets have become popular in urban areas (Weatherspoon & Reardon, 2003; Hawkes, 2008; Swinnen & Vandeplas, 2010), especially in Dar es Salaam (Ijumba et al., 2015), contributing to an increase in the consumption of ultra-processed foods and calories (Khonje et al., 2020).

3.5 Conclusion

Analysing dietary differences between rural and urban areas is key in an urbanizing Africa where issues of hunger and malnutrition are returning to the forefront. Our findings highlight a substantial difference in dietary composition, and therefore quality, in rural areas, secondary towns and Dar es Salaam. Households living in secondary towns tend to consume more than rural households, both in terms of macro- and micronutrients, and are therefore less likely to suffer from undernourishment and micronutrient deficiencies. Conversely, although households living in Dar es Salaam consume more calories and fats, they consume less protein, fiber and key vitamins and minerals. We therefore also accentuate the importance in distinguishing between various types of urban areas, as dietary patterns can vary substantially.

When controlling for possible mechanisms, we find that education, wealth and food prices have a significant impact on our results. The coefficients for unhealthy substances such as fat, saturated fat and sugar are smaller for both secondary towns and Dar es Salaam. Differences in vitamin and mineral consumption are also partly explained for secondary towns. Nevertheless, significant differences remain between rural consumption and that in DSM, especially in terms of micronutrients. Several mechanisms can therefore benefit from a more thorough analysis. First, our measures for market access and availability are relatively simplistic. More information on the distance to fresh food markets and supermarkets, as well as time travelled to these destinations is necessary.

Second, a better understanding of parental opportunity costs is required. Decisions on home-cooking, time management and job characteristics should be considered. Lastly, we need a better understanding of consumer preferences in order to understand consumer demand differences in rural and urban areas and how these are established.

Overall, smaller urban areas may be most successful in providing a nutritious diet. Small urban areas are prone to following similar, traditional diets to those in rural areas, but with the added benefits of greater diversity and availability of foods, higher education and higher income opportunities. Higher supermarket prevalence, changing cultural norms and accordingly adjusted consumer preferences may cause the shift to a less nutrient-dense diet in highly urbanized regions.

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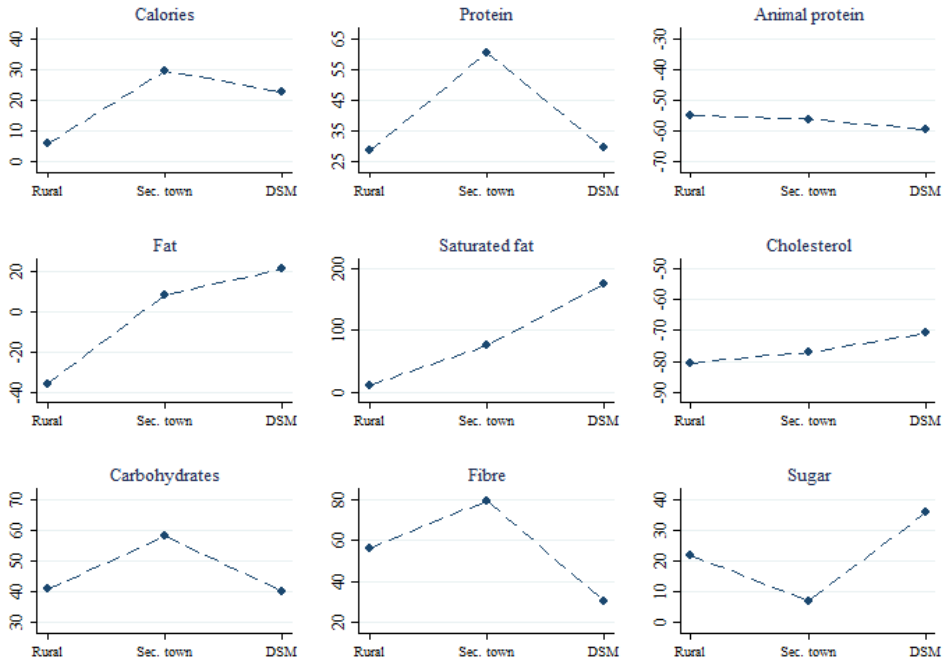
3.7 Figures

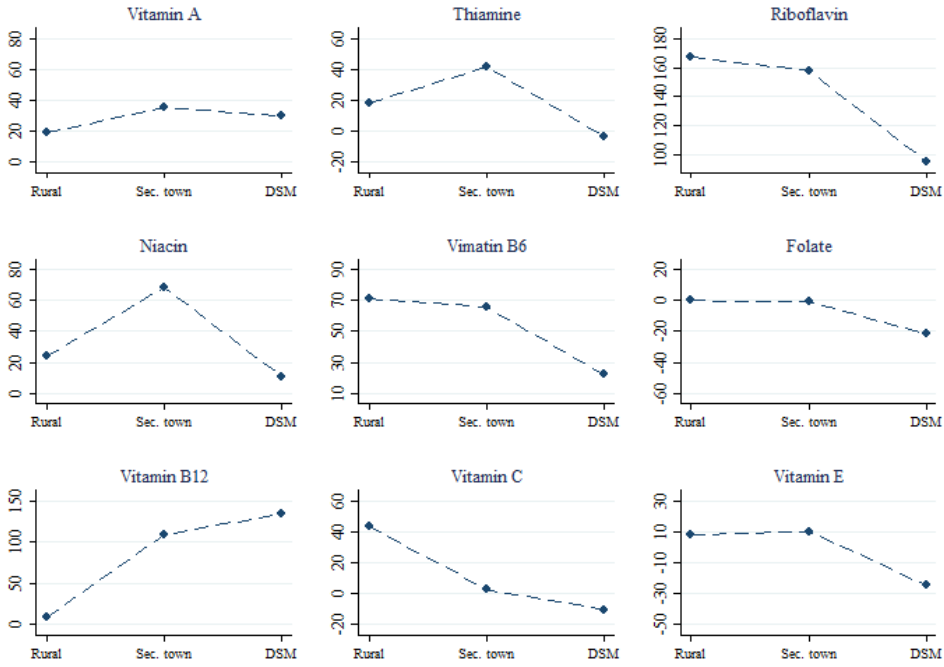
Figure 1 | Macronutrient, vitamin and mineral consumption by urban classification

Panel A: Macronutrient consumption relative to DRIs (%)

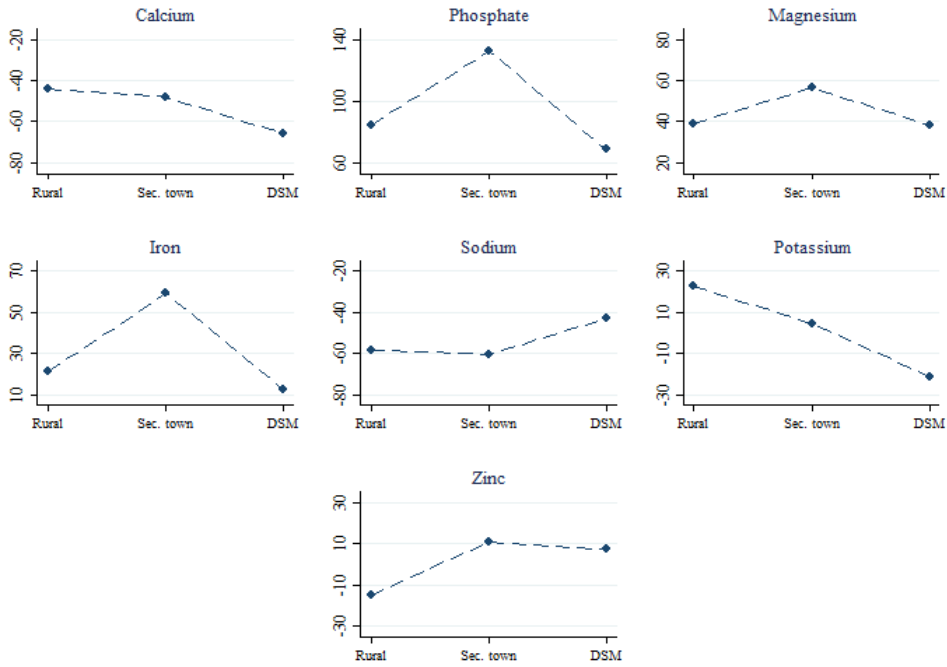


Note: Positive values represent the percentage by which the nutrient requirement is exceeded and negative values are the percentage shortfall from the requirements.

Panel B: Vitamin Consumption relative to DRIs (%)



Panel C: Mineral consumption relative to DRIs (%)



3.8 Tables

Table 1 | Rural-urban households per region

Region	Rural	Urban
Dodoma	27	187
Pwani	189	27
Dar es Salaam	0	214
Shinyanga	350	81
Kagera	422	9
Total	988	518

Table 2 | Household characteristics in rural and urban areas

Variable	Rural	Secondary towns	Dar es Salaam
Female household head	19.94	23.36	15.89
Age household head	47.72	47.38	41.79
Years of education household head	4.00	5.11	7.40
Household size	5.68	4.88	4.21
Married (hhh)	55.16	61.18	68.22
Polygamous (hhh)	21.15	8.88	7.01
Widowed (hhh)	14.57	16.45	7.48
Share children under 6	20.07	14.86	11.09
Share children between 6 and 15	26.28	22.55	15.95
Share adults over 65	8.03	9.21	3.04
Asset index (normalized)	0.20	0.38	0.66
Acres owned	4.43	3.33	1.70

Table 3 | Food group consumption in rural and urban areas[39]

	Percentage of total consumption		
Food groups	Rural	Secondary towns	Dar es Salaam
Cereals	16.40	19.07	16.76
Roots and tubers	13.59	9.38	7.16
Legumes	0.99	0.80	0.67
Nuts and seeds	3.28	4.68	3.03
Vegetables	17.73	15.17	10.49
Fruit	10.42	4.50	4.64
Meat	5.93	5.91	6.73
Seafood	1.49	1.35	0.97
Eggs	0.18	0.25	0.33
Dairy products	3.21	2.94	4.21
Meals outside	3.46	3.48	6.15
Snacks	4.25	5.74	7.96
Sugars and honey	4.84	4.45	6.47
Alcoholic drinks	5.81	7.51	5.64
Other drinks	7.42	13.72	17.76
Cooking oils and fats	0.98	1.04	1.02
Total	100	100	100

[39] Table A1 in the Appendix shows the average consumption in grams per individual food item consumed.

Table 4 | Regression results for nutrient consumption in rural areas, secondary towns and Dar es Salaam

VARIABLES	(1) Kcal	(2) Protein	(3) Fat	(4) Saturated Fat	(5) Cholesterol	(6) Carbohydrates	(7) Fiber	(8) Sugar
Secondary towns	23.73***	31.93***	44.00***	65.30***	3.456**	17.41***	23.32***	-14.86***
	(2.624)	(4.629)	(3.908)	(8.853)	(1.619)	(2.966)	(4.643)	(5.246)
Dar es Salaam	16.67***	0.874	56.77***	164.6***	9.612***	-0.702	-25.53***	13.88**
	(3.017)	(5.321)	(4.493)	(10.18)	(1.862)	(3.410)	(5.337)	(6.031)
Constant	5.801***	28.44***	-35.76***	10.93**	-80.47***	40.83***	56.24***	21.93***
	(1.273)	(2.245)	(1.896)	(4.295)	(0.785)	(1.439)	(2.252)	(2.545)
R-squared	0.060	0.032	0.137	0.156	0.018	0.024	0.039	0.011
VARIABLES	(9) Vitamin A	(10) Thiamine	(11) Riboflavin	(12) Niacin	(13) Folate	(14) Vitamin B12	(15) Vitamin C	(16) Vitamin E
Secondary towns	16.15*	23.20***	-9.562	44.73***	-0.916	100.0***	-41.27***	2.397
	(8.433)	(3.248)	(13.56)	(4.387)	(3.225)	(16.14)	(5.325)	(4.243)
Dar es Salaam	10.93	-21.74***	-71.75***	-13.47***	-21.21***	125.1***	-54.17***	-32.70***
	(9.695)	(3.734)	(15.59)	(5.043)	(3.708)	(18.55)	(6.122)	(4.878)
Constant	19.00***	18.04***	167.3***	23.98***	0.0357	9.750	43.97***	8.144***
	(4.091)	(1.576)	(6.577)	(2.128)	(1.565)	(7.827)	(2.583)	(2.058)
R-squared	0.003	0.066	0.014	0.078	0.022	0.044	0.071	0.031
VARIABLES	(17) Calcium	(18) Phosphorus	(19) Magnesium	(20) Iron	(21) Sodium	(22) Potassium	(23) Zinc	
Secondary towns	-3.947	47.54***	17.20***	37.82***	-2.201	-18.05***	25.99***	
	(2.432)	(6.010)	(3.545)	(4.041)	(2.090)	(2.521)	(2.904)	
Dar es Salaam	-21.80***	-16.28**	-1.047	-8.753*	15.28***	-43.92***	22.34***	
	(2.796)	(6.909)	(4.075)	(4.645)	(2.403)	(2.898)	(3.338)	
Constant	-44.10***	84.83***	39.28***	21.25***	-58.22***	22.67***	-14.92***	
	(1.180)	(2.915)	(1.719)	(1.960)	(1.014)	(1.223)	(1.409)	
R-squared	0.039	0.050	0.016	0.064	0.030	0.141	0.065	

Note: Standard errors in parentheses and *** p<0.01, ** p<0.05, * p<0.1. Each regression has 1,506 observations. Nutrient consumption is the percentage consumed above or below the dietary reference intake.

Table 5 | Regression results for nutrient consumption in rural areas, secondary towns and Dar es Salaam, with household controls

VARIABLES	(1) Kcal	(2) Protein	(3) Fat	(4) Saturated Fat	(5) Cholesterol	(6) Carbohydrates	(7) Fiber	(8) Sugar
Secondary towns	16.11***	16.40***	36.56***	54.13***	2.235	9.469***	7.130	-1.976
	(2.770)	(4.850)	(4.121)	(9.361)	(1.732)	(3.129)	(4.741)	(5.215)
Dar es Salaam	9.038***	-11.28**	44.89***	139.8***	6.281***	-5.492	-30.84***	10.53*
	(3.142)	(5.501)	(4.674)	(10.62)	(1.965)	(3.549)	(5.378)	(5.916)
Constant	38.20***	85.23***	8.406	95.89***	-67.26***	55.94***	85.80***	-10.25
	(5.644)	(9.882)	(8.397)	(19.08)	(3.530)	(6.376)	(9.662)	(10.63)
R-squared	0.109	0.095	0.183	0.197	0.044	0.075	0.147	0.168
VARIABLES	(9) Vitamin A	(10) Thiamine	(11) Riboflavin	(12) Niacin	(13) Folate	(14) Vitamin B12	(15) Vitamin C	(16) Vitamin E
Secondary towns	21.26**	13.01***	-31.35**	32.78***	-2.276	103.0***	-33.62***	1.913
	(8.996)	(3.357)	(14.25)	(4.644)	(3.418)	(17.40)	(5.463)	(4.488)
Dar es Salaam	7.800	-26.11***	-76.38***	-23.17***	-25.15***	112.3***	-55.80***	-37.13***
	(10.20)	(3.808)	(16.17)	(5.267)	(3.878)	(19.74)	(6.197)	(5.091)
Constant	-0.798	38.18***	146.5***	60.27***	1.129	35.47	-17.36	8.705
	(18.33)	(6.842)	(29.05)	(9.463)	(6.966)	(35.46)	(11.13)	(9.146)
R-squared	0.034	0.151	0.073	0.121	0.065	0.054	0.168	0.078
VARIABLES	(17) Calcium	(18) Phosphorus	(19) Magnesium	(20) Iron	(21) Sodium	(22) Potassium	(23) Zinc	
Secondary towns	-10.75***	24.59***	10.23***	21.40***	-2.981	-14.64***	17.95***	
	(2.553)	(6.162)	(3.754)	(4.079)	(2.220)	(2.579)	(3.075)	
Dar es Salaam	-24.50***	-28.23***	-8.315*	-16.09***	11.78***	-45.84***	15.06***	
	(2.896)	(6.989)	(4.258)	(4.627)	(2.518)	(2.925)	(3.488)	
Constant	-24.91***	152.6***	62.03***	61.70***	-37.11***	11.78**	11.18*	
	(5.202)	(12.56)	(7.650)	(8.313)	(4.524)	(5.255)	(6.267)	
R-squared	0.099	0.150	0.061	0.188	0.068	0.235	0.107	

Note: Standard errors in parentheses and *** p<0.01, ** p<0.05, * p<0.1. Each regression has 1,506 observations and contains household controls (female household head, age of household head, household size, share of children younger than 6, whether the household head is married, polygamous or widowed and month interviewed control).

Table 6 | Regression results including possible pathways for the difference in nutrient consumption between rural areas, secondary towns and Dar es Salaam

Panel A: Macronutrients

VARIABLES	(1) Kcal	(2) Protein	(3) Fat	(4) Saturated Fat	(5) Cholesterol	(6) Carbohydrates	(7) Fiber	(8) Sugar
Secondary towns	3.408	-9.941*	-18.27***	18.91***	25.96**	-7.103***	1.964	-3.394
	(3.354)	(5.741)	(3.706)	(4.943)	(10.86)	(2.049)	(3.803)	(5.510)
Dar es Salaam	-34.86***	-117.2***	-46.87***	1.614	129.2***	-16.38***	-41.68***	-111.7***
	(6.851)	(11.72)	(7.569)	(10.10)	(22.18)	(4.185)	(7.767)	(11.25)
Wealth (asset index)	10.59	-15.04	7.781	57.68***	196.1***	22.08***	-13.02	-55.06***
	(7.276)	(12.45)	(8.040)	(10.72)	(23.56)	(4.444)	(8.249)	(11.95)
Years of education (hhh)	0.737**	1.580***	1.327***	2.291***	5.123***	1.302***	0.169	-0.261
	(0.337)	(0.576)	(0.372)	(0.496)	(1.090)	(0.206)	(0.382)	(0.553)
Restaurant in cluster (dummy)	4.694*	7.106	7.514**	3.535	12.76	4.353**	1.943	-3.270
	(2.767)	(4.735)	(3.057)	(4.077)	(8.956)	(1.690)	(3.137)	(4.545)
Shops/stalls in cluster (dummy)	0.161	5.076	4.775*	1.184	-0.533	0.750	-1.635	-2.711
	(2.577)	(4.411)	(2.848)	(3.798)	(8.344)	(1.574)	(2.922)	(4.234)
Market in cluster (dummy)	4.992	5.535	3.509	1.307	8.369	-2.175	8.450**	2.295
	(3.179)	(5.441)	(3.513)	(4.685)	(10.29)	(1.942)	(3.605)	(5.223)
Price index	0.236***	0.716***	0.155***	0.0584	-0.717***	0.0538**	0.275***	0.774***
	(0.0377)	(0.0644)	(0.0416)	(0.0555)	(0.122)	(0.0230)	(0.0427)	(0.0619)
Constant	-38.21***	-129.2***	-86.49***	-39.09**	212.3***	-98.19***	-20.77	-116.2***
	(12.37)	(21.17)	(13.67)	(18.23)	(40.04)	(7.555)	(14.02)	(20.32)
R-squared	0.143	0.169	0.062	0.230	0.292	0.118	0.105	0.245

Panel B: Vitamins

VARIABLES	(1) Vitamin A	(2) Thiamine	(3) Riboflavin	(4) Niacin	(5) Folate	(6) Vitamin B12	(7) Vitamin C	(8) Vitamin E
Secondary towns	-36.97***	2.700	-99.14***	12.86**	-17.89***	-2.469	-13.69	-16.32**
	(10.63)	(3.832)	(16.67)	(5.420)	(5.202)	(4.187)	(20.55)	(6.698)
Dar es Salaam	-168.1***	-94.51***	-399.6***	-124.7***	-111.6***	-36.91***	-220.1***	-9.127
	(21.72)	(7.827)	(34.04)	(11.07)	(10.62)	(8.552)	(41.96)	(13.68)
Wealth (asset index)	120.7***	-48.88***	24.68	-32.45***	-25.51**	-11.24	317.2***	-51.32***
	(23.07)	(8.313)	(36.16)	(11.76)	(11.28)	(9.083)	(44.57)	(14.53)
Years of education (hhh)	5.814***	0.121	0.901	1.222**	1.184**	1.190***	9.219***	0.248
	(1.068)	(0.385)	(1.674)	(0.544)	(0.522)	(0.420)	(2.063)	(0.673)
Restaurant in cluster (dummy)	-5.885	1.500	-18.85	-0.497	-2.033	-4.389	-11.16	-6.835
	(8.770)	(3.161)	(13.75)	(4.471)	(4.291)	(3.454)	(16.95)	(5.525)
Shops/stalls in cluster (dummy)	28.17***	-2.685	8.425	-0.0435	1.812	-1.918	41.38***	-2.584
	(8.170)	(2.945)	(12.81)	(4.165)	(3.997)	(3.218)	(15.79)	(5.147)
Market in cluster (dummy)	-21.33**	5.563	-26.49*	4.707	-0.197	-5.951	-3.678	0.291
	(10.08)	(3.632)	(15.80)	(5.138)	(4.931)	(3.969)	(19.47)	(6.349)
Price index	0.716***	0.634***	2.309***	0.794***	0.455***	0.132***	1.056***	-0.144*
	(0.119)	(0.0430)	(0.187)	(0.0608)	(0.0584)	(0.0470)	(0.231)	(0.0752)
Constant	-278.3***	-130.2***	-512.2***	-165.0***	-56.84***	-39.08**	-412.9***	36.84
	(39.21)	(14.13)	(61.46)	(19.99)	(19.18)	(15.44)	(75.76)	(24.70)
R-squared	0.116	0.275	0.169	0.215	0.153	0.081	0.136	0.180

Panel C: Minerals

VARIABLES	(1) Calcium	(2) Phosphorus	(3) Magnesium	(4) Iron	(5) Sodium	(6) Potassium	(7) Zinc
Secondary towns	-17.82***	-6.863	5.990	6.028	-10.17***	-11.94***	5.605
	(3.027)	(7.062)	(4.617)	(4.698)	(2.699)	(3.166)	(3.744)
Dar es Salaam	-64.77***	-182.0***	-29.88***	-105.0***	-15.86***	-45.24***	-20.91***
	(6.182)	(14.42)	(9.430)	(9.595)	(5.512)	(6.465)	(7.647)
Wealth (asset index)	-22.43***	-53.41***	-12.16	-39.19***	8.851	-15.52**	18.61**
	(6.566)	(15.32)	(10.02)	(10.19)	(5.854)	(6.867)	(8.122)
Years of education (hhh)	-0.162	0.768	0.212	0.205	0.713***	0.816**	1.169***
	(0.304)	(0.709)	(0.464)	(0.472)	(0.271)	(0.318)	(0.376)
Restaurant in cluster (dummy)	-2.862	3.247	2.609	-1.004	1.528	-4.758*	2.684
	(2.496)	(5.825)	(3.808)	(3.875)	(2.226)	(2.611)	(3.088)
Shops/stalls in cluster (dummy)	4.065*	3.576	-0.246	-0.670	-3.517*	-1.604	3.752
	(2.326)	(5.427)	(3.548)	(3.610)	(2.074)	(2.432)	(2.877)
Market in cluster (dummy)	3.010	11.18*	0.313	3.138	4.386*	-0.480	3.051
	(2.869)	(6.694)	(4.377)	(4.453)	(2.558)	(3.001)	(3.549)
Price index	0.348***	1.201***	0.181***	0.755***	0.152***	0.0510	0.142***
	(0.0340)	(0.0793)	(0.0518)	(0.0527)	(0.0303)	(0.0355)	(0.0420)
Constant	-117.8***	-182.8***	11.70	-143.3***	-86.73***	-2.455	-44.08***
	(11.16)	(26.04)	(17.03)	(17.32)	(9.951)	(11.67)	(13.81)
R-squared	0.170	0.268	0.069	0.294	0.097	0.244	0.133

Note: Standard errors in parentheses and *** p<0.01, ** p<0.05, * p<0.1. Each regression has 1,506 observations and contains household controls (female household head, age of household head, household size, share of children younger than 6, whether the household head is married, polygamous or widowed, price index and month interviewed control) and pathways. Nutrient consumption is the percentage consumed above or below the dietary reference intake.

3.9 Appendix

Table A1 | Percentage of each food item consumed in rural and urban areas

	Rural		Secondary towns		Dar es Salaam	
Food item	Mean (grams consumed per capita)	Standard deviation	Mean (grams consumed per capita)	Standard deviation	Mean (grams consumed per capita)	Standard deviation
Rice (paddy)	102.10	232.11	90.61	188.48	20.29	25.83
Rice (husked)	38.86	57.53	82.25	105.19	125.50	154.79
Maize (green, cob)	27.12	39.06	12.91	14.60	10.27	8.75
Maize (grain)	126.52	191.76	173.75	213.40	94.26	130.13
Maize (flour)	65.64	109.49	95.31	123.91	135.70	143.62
Millet and sorghum (grain)	124.17	193.57	102.34	129.57	43.49	114.94
Millet and sorghum (flour)	61.40	85.88	71.22	107.83	25.77	28.30
Wheat, barley grain and other cereals	32.30	63.79	59.90	100.74	52.19	84.64
Bread	8.37	14.46	6.81	12.24	50.30	80.32
Buns and biscuits	5.84	12.15	2.52	4.95	13.09	47.63
Macaroni, spaghetti	10.45	9.64	39.91	76.01	26.52	23.19
Cassava fresh	110.50	157.01	102.58	132.81	81.00	103.45
Cassava dry/flour	82.89	141.80	80.60	115.30	38.78	60.23
Sweet potatoes	78.26	118.43	60.60	80.25	57.82	48.62
Yams	57.29	78.10	77.35	91.75	44.00	37.10
Irish potatoes	33.85	56.10	41.65	64.85	33.60	65.72
Other starches	136.72	122.59	0.00	0.00	0.00	0.00
Cooking bananas, plantains	167.79	233.40	50.09	87.13	31.08	54.03
Peas, beans and other pulses	36.57	56.88	30.88	56.60	23.75	40.76
Groundnuts in shell/shelled	20.69	55.63	31.26	112.44	14.69	31.38
Coconuts (mature/immature)	49.19	64.78	52.61	60.15	82.40	63.64
Cashew, almonds and other nuts	34.18	45.81	0.00	0.00	10.98	10.77
Seeds	16.36	14.55	97.26	173.83	0.00	0.00
Green pepper, okra	13.67	22.13	14.91	23.76	11.48	15.16
Onions	17.58	41.29	22.19	26.50	17.13	19.02
Tomatoes	31.55	58.48	66.74	69.97	69.67	50.15
Carrots	4.08	3.47	16.17	20.29	8.89	13.13
Eggplant, zucchini	13.52	16.72	9.31	9.81	5.96	4.86
Pumpkin	183.86	206.46	194.68	229.23	127.00	160.67
Cabbage	30.16	29.67	28.61	19.12	24.63	21.65

Spices, leaves and flowers	20.00	33.66	14.55	21.65	7.37	9.55
Spinach and other leaves	45.51	70.36	30.74	49.50	22.26	23.29
Cassava leaf	32.60	34.58	32.71	42.25	25.76	24.35
Canned, dried and wild vegetables	23.95	40.47	32.30	36.00	0.00	0.00
Other vegetables	67.61	82.62	73.64	110.65	22.76	18.61
Ripe bananas	75.81	158.21	12.47	19.60	13.22	22.02
Oranges, tangerines	50.20	88.10	22.93	28.39	46.04	66.87
Lemons, limes	32.25	81.99	14.99	17.46	13.25	20.24
Pineapple	3.66	9.68	3.97	4.01	3.09	2.23
Fruit	13.64	31.89	9.02	11.94	35.35	62.15
Papaya	8.90	18.41	4.23	4.44	5.62	7.57
Avocado	17.49	47.48	7.36	10.36	9.34	15.03
Mangos	113.61	197.90	44.57	89.24	8.05	11.21
Durian	1.94	3.53	1.26	0.00	2.13	1.09
Melons	3.44	3.32	5.25	8.56	13.17	16.71
Cucumbers	18.79	33.79	12.13	18.98	4.37	5.02
Apple	22.93	40.32	26.05	77.53	3.13	0.00
Pear	20.45	23.03	9.67	12.79	8.77	10.70
Sugarcane	125.44	155.47	134.04	151.33	196.42	206.42
Goat meat	25.35	32.08	28.53	25.78	34.04	25.93
Soup, meat broths	24.03	82.15	13.13	19.73	19.96	30.96
Beef including minced sausage	32.16	44.93	47.20	53.99	48.84	49.48
Bacon/Pork	27.63	41.97	30.64	17.35	12.36	6.97
Chicken and other poultry	66.64	77.36	84.29	70.50	124.61	113.06
Wild birds, edible insects	15.96	34.71	13.90	11.49	0.00	0.00
Other domestic/wild meat products (rabbit)	26.36	37.15	11.07	15.05	0.00	0.00
Eggs	6.50	12.20	9.77	12.79	11.83	16.27
Fresh fish and seafood	31.03	45.76	29.58	46.05	26.44	26.06
Dried/fish and seafood	23.89	37.38	22.80	27.07	8.08	11.15
Fresh milk	87.34	98.76	65.50	86.42	52.95	63.70
Yoghurt	26.99	31.66	41.69	48.05	33.27	38.84
Milk powder	3.70	3.89	6.38	0.00	63.82	70.18
Palm oil	12.63	19.01	8.00	9.75	0.00	0.00
Cooking oil	11.94	18.18	23.80	33.81	25.78	32.35
Butter, margarine, ghee and other fat products	11.56	13.42	8.41	7.89	10.51	8.07
Tea (leaves or prepared)	15.99	24.83	21.70	27.99	28.14	32.98
Coffee and cocoa	5.25	15.12	9.54	10.10	27.55	28.21
Water	230.10	276.13	466.83	263.56	536.48	244.91

Juice	9.52	18.91	13.20	17.11	16.44	17.12
Bottled beer	23.69	33.41	37.46	40.68	99.71	111.73
Local brews	82.74	119.05	90.21	88.38	10.15	0.00
Wine and spirits	13.71	28.08	0.00	0.00	0.00	0.00
Kibuku and local brews	67.28	92.73	154.98	190.34	0.00	0.00
Alcoholic drinks	26.21	42.53	7.95	9.92	91.31	77.48
Sodas (Carbonated drinks)	11.99	16.02	19.53	22.07	24.52	22.10
Sugar	22.16	29.08	26.31	31.78	28.23	32.05
Honey	30.35	41.21	11.79	10.17	5.82	3.15
Sweets (candy, chocolate)	1.09	1.36	1.05	1.32	1.44	2.70
Full meals (Av. of known meals)	21.91	70.92	47.63	103.18	82.38	144.26
Cereal with banana	30.33	49.65	0.00	0.00	0.00	0.00
Porridge meal	12.63	34.70	13.98	22.38	33.80	63.94
Maharage (banana and kidney bean dish)	42.85	75.83	33.67	43.45	42.24	50.03
Makande (maize and kidney bean dish)	8.15	9.33	19.35	18.73	13.40	4.53
Wali (rice with coconut milk dish)	11.18	21.33	19.99	49.03	47.52	65.51
Chips, fried/roasted potatoes	11.16	17.52	8.25	12.95	13.83	19.88
Popcorn	13.63	9.59	45.79	62.55	16.68	14.16
Meat skewer barbequed	10.46	9.26	12.38	9.12	13.28	13.08
Roasted/fried banana	11.76	14.42	11.70	11.26	10.87	3.79
Fried/Roast beef	7.41	4.77	10.20	9.68	30.25	48.23
Ice cream and sherbet	0.91	1.88	0.62	0.66	0.78	0.89
Snacks (Av. of all other snacks)	18.30	22.15	22.43	30.44	19.61	24.64
Rice bun	6.44	13.97	18.85	28.86	20.17	21.98
Samosa	6.06	6.06	8.35	7.85	22.23	27.28
Fried Cassava	28.33	65.11	19.43	21.65	30.24	28.36
Donut, African donut	8.07	15.60	21.25	28.28	31.15	36.00
Groundnut cluster	0.58	0.40	1.15	1.35	1.00	1.03
Cake	4.01	4.20	5.27	8.90	6.75	9.39
Chapati	9.63	22.74	20.16	31.93	45.86	61.25
Bagia (chickpea fritters)	18.45	26.63	15.12	13.82	19.38	16.66
Total	3675.72		3867.76		3564.09	

Table A2 | Percentage of households consuming under the DRI

	Rural	Secondary towns	Dar es Salaam
Calorie	47.67	26.64	38.32
Macronutrients			
Protein	40.99	21.05	35.98
Animal protein	90.59	90.46	90.19
Fat	83.81	60.86	48.13
Saturated fat	61.94	36.84	12.15
Cholesterol	98.79	98.03	95.79
Carbohydrate	18.12	14.47	27.57
Sugar	48.99	52.63	31.31
Fiber	21.96	16.78	32.71
Vitamins			
Vitamin A	57.19	54.93	55.61
Thiamine	42.51	27.96	56.54
Riboflavin	18.93	12.50	21.03
Niacin	40.89	22.04	46.26
Vitamin B6	7.09	15.46	39.72
Folate	63.36	61.84	76.17
Vitamin B12	71.46	49.67	42.99
Vitamin C	34.11	57.57	65.89
Vitamin E	56.28	57.24	78.04
Minerals			
Calcium	87.85	91.12	99.07
Phosphate	18.32	8.55	16.82
Iron	45.75	24.67	46.73
Sodium	94.03	97.70	89.72
Potassium	26.62	48.36	75.70
Magnesium	20.55	19.41	25.70
Zinc	70.34	45.39	46.73
Observations	988	304	214

Chapter 4. The rising price of nutritious foods: The case of Ethiopia*

4.1 Introduction

In 2020, 1 in 9 people globally are undernourished, over 2 billion people face micronutrient deficiencies and 1 in 3 people are found to be overweight or obese (Development Initiatives, 2020). These coinciding forms of malnutrition are highly alarming consequences of flawed food consumption patterns. There is a heightened need to find a new balance in diets, whilst also realizing their need to be sustainable. The highly influential recommended EAT-Lancet diet therefore provides guidelines on dietary practices that are both nutritionally and sustainably optimal (Willett et al., 2019). However, a shift towards these diets requires foods to be both available and affordable (Darmon & Drewnowski, 2015).

In developed countries, many studies highlight how nutrient-dense foods can be relatively more expensive (Drewnowski, 2010; Headey & Alderman, 2019). In particular, the link between obesity and the lack of access and consequent high prices of healthy foods has been explored (e.g. Han & Powell, 2011; Aggarwal et al., 2012; Xu et al., 2014; Powell et al., 2013), although demand and consumer preferences are also highly important in the choice of diet (Allcott et al., 2019). In emerging economies, several studies have also documented rapid increases in the cost of healthy diets (e.g. Wiggins et al., 2015; Masters et al., 2018). More specifically, Hirvonen et al. (2020) find the EAT-Lancet diet to be much less attainable in lower income regions. The predominantly high cost of fruits, vegetables and animal-sourced foods causes a particular barrier to the consumption of a nutritionally sound diet. Given the high prevalence of undernutrition among children in low income countries, and the associated high human and economic costs (Hoddinott et al., 2013), improving nutritional outcomes is an urgent priority. Therefore, understanding food price evolutions across time and factors influencing these prices is important to inform appropriate food policies.

* This chapter is co-authored by Fantu Nisrane Bachewe and Bart Minten.

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In this paper, we investigate the price formation of nutritious foods in Ethiopia, the second most populous country in Africa, from 2005 to 2018. Improving nutrition is high on the Ethiopian government's policy agenda aiming to reduce child stunting levels (at 40 percent in 2014/15), but despite recent improvements, child stunting in Ethiopia remains widespread (CSA and ICF International, 2017). Moreover, Ethiopian children consume one of the least diverse diets in sub-Saharan Africa (Hirvonen, 2016). At the household level, food consumption baskets are dominated by cereals and pulses, while the consumption of animal-source foods and micronutrient-rich fruits and vegetables is rare, especially in rural areas (e.g., Worku et al., 2017; Hirvonen et al., 2017). Such monotonous diets are regarded as a major contributor to malnutrition as well as to the incidence of non-communicable diseases (Melaku et al., 2016).[40]

We analyze the price evolution of different food groups in Ethiopia using large-scale nationally representative price datasets. We find that the price of nutritious foods has significantly worsened between 2005 and 2018. The price of legumes, nuts, green leafy vegetables, other fruit and vegetables, and animal products increased by between 23 and 74 percent over the period studied. This increase in the price of nutritious foods falls in contrast with staple crops - i.e. grains, roots and tubers - where an increase of only 6 percent is seen over the same period. On the other hand, we see a significant decline for foods traditionally associated with obesity, such as oils and sugar, with observed real price declines of 41 and 49 percent respectively. These are worrying signs for stakeholders interested in improving nutritional outcomes in the country.

We then analyze factors linked to the observed trends in food prices. Our results show highly significant associations between the price of nutritious foods and their price in areas with a comparative advantage in the production of these items, along with prices in urban areas. Cross-border trade also highly influences the price of nutritious foods, especially so for non-perishable ones. Moreover, we find that local production changes only slightly affect nutritious food prices, possibly due to relatively good market integration in the country. Cooking oils and sugar prices are highly associated with prices in Addis Ababa, an indication of centralized government procurement or production (for sugar) and distribution, and ongoing price controls for those products. Finally,

[40] Recent research in Ethiopia suggests that the poor dietary diversity in rural areas can be explained, at least partly, both by limited knowledge about the health benefits of diverse diets and by poor access to food markets. Households in areas in which food crop production is not very diverse but which have good access to markets are found to have more diverse diets than households in areas with similar production patterns but with poor access to markets and, so, depend primarily on own-production for the food they consume (Hoddinott et al., 2015; Abebe et al., 2016; Kim et al., 2016; Zerfu et al., 2016; Hirvonen & Hoddinott, 2017; Hirvonen et al., 2017; Stifel & Minten, 2017; Abay & Hirvonen, 2017).

changes in transaction costs – fuel and transport costs – are found to be less related to price changes for any food.

Our results have a number of implications. First, given the large influence of prices on consumer choices of food in countries like Ethiopia, more investments and attention to the local production of nutritious foods is needed to reduce their price and improve their affordability for consumers. Focus should not only be on production by the household itself – e.g., households might not have access to appropriate water supplies, shown to be an important determinant of the successful adoption of vegetable homestead gardening (Hirvonen & Headey, 2018) – or in the locality in which they live, but more importantly on production in commercial clusters with comparative advantages in the production of such nutritious crops.

Second, market and trade policies also play a role in regulating prices. Border price effects have an important influence on nutritional foods, in particular for livestock products and some vegetables (e.g. onions). These effects are less prominent for cereal crops where typically little or no cross-border trade has happened over the period considered (except for wheat, which is often used towards food aid). The effects of exchange rate changes on agricultural commodity prices are found for all crops, although more prominent for cereals. These effects are both direct, and indirect i.e. through the costs of intermediary inputs such as chemical fertilizers, agro-chemicals, hybrid seeds, and improved feed ingredients.

Third, government placed price caps, direct government distribution through kebele (village) shops, and subsidies for those foods that are traditionally associated with obesity, such as oils and sugar, - for a description of government policies in these areas, see Assefa et al. (2016) - should best be relaxed so they can better reflect the true cost of these items. [41] As these unhealthy items become cheaper, people are likely to substitute away from more expensive mineral and vitamin rich foods to calorie-dense cheap foods, decreasing the quality of their overall diets and in turn health. While obesity is less of an issue in Ethiopia than in other countries, it is an emerging public health problem (Gebru et al., 2018; Ameye & Swinnen, 2019).

[41] Ethiopia partly changed policies in this area (February 2020) and Parliament approved a tax on sugary drinks, products high in saturated and trans-fat, alcohol, and tobacco.

4.2 Price trends of nutritious and other foods

4.2.1. Data

First, we use monthly price data from January 2005 to December 2018 collected by the Central Statistical Agency (CSA) of Ethiopia under its periodic Consumer Price Survey. Prices are collected from 116 markets in all regions (but not all zones) of Ethiopia. CSA enumerators – who permanently reside near these markets – collect price data from traders, retailers and consumers. To ensure a sufficient degree of national representativeness, the number of surveyed markets in each region is approximately proportional to the region's share of the total urban population. Figure 1 presents the retail markets included in this study relative to the population density across Ethiopia. To ensure comparability of prices over time and to remove the effect of general inflation on prices, we compute real prices by deflating nominal prices observed in the markets by the regional General Consumer Price Index (CPI), calculated by CSA. We express all prices in December 2011 birr terms (CSA 2017).[42] This means that the prices reported here are relative to the price of the average consumption basket for the country.

Dietary quality is often proxied by dietary diversity. The literature typically adopts various numbers of food groups to measure dietary diversity for different demographic groups.[43] The common feature of these approaches is to group food items according to the key nutrients they provide. Following this approach, we study the price evolution of ten food groups: grains, roots and tubers; legumes and nuts; dairy products; eggs; flesh foods and small animal protein; vitamin A-rich dark green leafy vegetables; other vitamin A-rich vegetables and fruits; other fruits and vegetables; oils and fats; sugar and honey (Table 1). Households or individuals regularly consuming foods from a greater number of these food groups are more likely to meet their needs in terms of both macro- (e.g. carbohydrates, protein) and micronutrients (e.g. vitamin A, iron, zinc).

Second, we use the 2011 national Household and Consumption Expenditures Survey (HCES) data to identify the food items in each food group and to

[42] The evolution of general, food and non-food CPI between 2005 and 2018 can be found in the Appendix (Figure A1).

[43] For example, WHO (2008) recommends a 7-food group indicator for children 6-24 months of age. FAO and USAID's Food and Nutrition Technical Assistance III Project (FANTA) proposes a 10-food group indicator to assess women's dietary diversity (FAO & FHI360, 2016) and a 12-food group indicator for household level analysis (Swindale & Bilinsky, 2006).

compute the average share of each item in the total weight of per capita consumption of each food group at the administrative zone level.[44] Table 1 lists the number of items in each food group in the HCES data and those with price information in the CSA dataset. Out of the 211 items included in all food groups in the HCES data (Table 1, column 2), price information is available for about half (106) of them (column 3). Nevertheless, the price data comprise the most commonly consumed items, accounting for a majority share of the total weight in each food group (Table 1, column 4).[45] Table 1 shows that, overall, we can account for the price evolution of 83 percent of the average consumption basket (column 4, last row).

For each of the ten food groups we calculate a weighted average price using the Laspeyres index method, where prices adjust while the importance of items in the food group per capita quantity consumed are assumed to be constant at 2011 (middle of the study period) levels.[46] The weighted real price of food group (f) in zone (z) in any given month (t) is calculated as:

$$Real\ price_{fzt} = \sum_{i=1}^{I} Real\ price_{izt} * PCCW_i \text{ where } i = 1, 2, \dots, I$$

where $Real\ price_{izt}$ is the real price of item i in zone z and month t; $PCCW_i$ stands for the weight of i in per capita quantity of food group (f) consumption and $i = 1, 2, \dots, I$ indicates that the food group price is a sum of weight*price over the items in the food group. For instance, the price of the food group grains, roots and tubers is the average price of 34 items (Table 1, column 3) weighted by their importance in per capita consumption.

4.2.2. Price trends of nutritious foods and other foods

Figures 2 and 3 depict how the real consumer prices of different food groups have changed over the study period in Ethiopia. Figure 2 shows price trends for plant-based foods, while Figure 3 shows price trends for animal-source foods, oils and fats, and sugar and honey.[47] All price indices are set to 1.0 in January 2005, the first month in the price data series used here. Price index values above 1.0 mean that the real food group prices have increased, while values below 1.0 imply that food group prices have become cheaper over time, in real terms.

[44] HCES is the official source of poverty statistics in Ethiopia.

[45] For instance, although price data are only available for indigenous hens' eggs, the other item in this food group, hybrid hens' eggs, accounted for less than 6 percent of the consumption of eggs.

[46] For more information on the construction of prices indices, see Deaton and Tarozzi (2000).

[47] A 12-month centered moving average (MA) was used to smoothen out seasonal movements. Given the complication of an even number of months in a year, in a centered MA, we take two consecutive moving averages and average these.

Figures 2 and 3 show that over the study period, monthly prices increased for eight of the ten food groups. The largest price increases are observed for vitamin A-rich dark green leafy vegetables – real prices for this food group nearly doubled between January 2005 and December 2018, with a spike in 2011 and then further taking off (Figure 2). Prices of foods in the other vitamin A-rich fruits and vegetables group increased by 40 percent, and prices of other fruits and vegetables increased by about 24 percent over the same period. The price index for legumes and nuts displayed considerable volatility over the last decade – real prices of legumes and nuts dipped in 2009 and in mid-2014, but by December 2018 they were more than 32 percent higher than in 2005. These price trends fall in contrast with the real prices of grains, roots and tubers, the most important components of the total consumption basket in Ethiopia, which at the end of 2018 were only slightly above prices in 2005.[48]

From Figure 3 we see that the monthly price of all animal-source food categories increased substantially. The real price of dairy, eggs and meat increased between 44 and 84 percent over the time period. Even more noteworthy, is the complete opposite price trajectory for oils and fats, and sugar and honey food groups. Figure 3 shows a 45 percent decrease in the prices of both these food categories, traditionally associated with rising obesity (Popkin et al., 2012). While obesity is less of an issue in Ethiopia than in other countries, it is an emerging problem with 8 percent of adult women nationally, and 21 percent in urban areas being overweight or obese (CSA & ICF International, 2017). Related, an increasing number of Ethiopians are struggling with high blood pressure and diabetes (FMoH/UNICEF/EU, 2016).

Table 2 further portrays the evolution of the annual median urban retail price as the total percentage change in real prices between 2005 and 2018. Reflecting the patterns found in Figure 2 and 3, the most prominent price increases are found for meat (70%) and green leafy vegetables (74%), two of the most nutrient dense food groups. We find that prices of sugar and honey decreased by 49 percent during this period, while oils and fats decreased by 41 percent (Table 2), a worrying trend.

4.3 Contributing factors to food price changes

The cost of a nutritious diet containing fruit, vegetables and animal products is rising, whereas the cost of staple grains remains steady and the cost of unhealthy substances such as oils and sugar is falling. It is therefore imperative to gain

[48] Prices of grains, tubers, and roots were higher in 2008 and 2009, and again in 2011, possibly linked to the international food price crisis.

some understanding of factors influencing these price differences, especially as these trends lead towards an unhealthy lifestyle, increasing health risks.

4.3.1. Data

We continue with an econometric analysis to study factors associated with the real retail prices of 14 of the 106 food items for which prices are collected in the Consumer Price Survey (Table 1). We use three criteria to determine which items are included in the econometric analyses. First, each food group is represented by at least one item. Second, items are selected based on their importance in total per capita consumption of their respective food group. Third, the continuous availability of retail prices must be ensured. The 14 selected items represent all ten food groups listed in Table 1 except for "Other vitamin A-rich vegetables and fruits", which are excluded from the analyses due to limited price data. The items selected from the remaining nine food groups are: Grains, roots and tubers: teff, maize, and wheat; Legumes and nuts: field peas and horse beans; Dairy products: milk; Eggs; Flesh foods and small animal protein: beef; Vitamin A-rich dark green leafy vegetables: kale; Other fruits and vegetables: onion, bananas, and tomatoes; Oils and fats: cooking oil; Sugar and honey: sugar. These food items are then sorted into three categories, i.e. cereals, nutritious foods, and cooking oil and sugar.

Next, several factors may be associated with price changes for cereals, nutritious foods, and oils and sugar. First, access to infrastructure and proximity to markets influences the flow of food to and from a given locality and, thus, are important determining factors of food prices in the locality. We assume that local real food prices are associated with the density and quality of roads serving the locality and its proximity to urban centers. We account for this by including travel time in our models. Travel time is constructed using district level data on the length and type/quality of roads and the distance between the center of each district to an urban center with a population of 50,000 or higher. Out of the years covered in the analyses, 2005 to 2018, data on roads are available for three of them – 2007, 2010, and 2015. Consequently, travel time is calculated for these three years and linearly interpolated for the remaining years. Food prices are also assumed to be associated with transportation costs. Monthly retail fuel price data collected through the Consumer Price Surveys are used to proxy transportation costs.

Second, prices of a given item are associated with the supply of the item within the locality. We account for this factor by using per capita output of the

item in the zone.[49] However, given output levels can both influence and be influenced by prices, i.e. they are endogenous, we use the predicted value of outputs to compute per capita output. Following Shively and Thapa (2016), we use the quantity of rainfall during the crop season, travel time, number of oxen, which are an important source of plowing power in Ethiopia, and zonal and period dummies as independent variables in the regression analyses conducted to predict each crop output. Similarly, in the regression analyses used to predict animal-source foods production, we use the mean travel time, animal stock used in the production of the item, percent of animal deaths due to diseases and other factors, and zonal and period dummies as independent variables.[50]

Third, food prices are expected to increase with increases in demand for the item. We use the population density per total crop area in each zone as a measure for food demand. We also include the average zonal wage level of unskilled labor to proxy general wage evolutions throughout this time. Here we will use lagged wage values as the wages of previous months are more likely to influence current price changes than current wages.

Fourth, a large majority of the cities and towns from which the retail price data are collected are connected with Addis Ababa, by far the largest city in Ethiopia, where almost 40 percent of the country's urban population resides (Schmidt et al., 2018). Therefore, prices in Addis Ababa are assumed to be important price setters for each locality and are used as an independent variable in the food price equations.

Fifth, Ethiopia conducts formal cross-boundary trade with Djibouti, Kenya, Somalia, Somaliland (Northern Somalia), South Sudan and Sudan. Moreover, anecdotal evidence indicates that considerable informal trade is also conducted with these countries. Traders collect food items and livestock destined for these countries from many areas in Ethiopia. As a result, local prices are expected to be associated with the price of items in these countries. We proxy the prices in neighboring countries by constructing average prices of the items in administrative zones bordering the six neighboring countries listed.

Sixth, Ethiopia has diverse cropping systems, and different districts focus on the production of different food items depending, among others, on climate, the food culture, and the productivity of the area. The local price of food items are assumed to be associated with the price of those items in areas with a comparative advantage in their production. To account for this effect, we include

[49] It would also be interesting to examine the relationships with labor and productivity costs, however no such data is available or compatible with our dataset.

[50] The results from these production functions can be found in Table A2 for crops and Table A3 for animal products in the Appendix.

the average price of each item in high productivity areas into our analysis.[51] We refer to these prices as the commercial cluster price.[52]

Seventh, exchange rate movements are related to overall levels of food prices, whether these items are traded or not (Krueger et al., 1988; Barrett, 1997). We account for this influence on local food prices using the real exchange rate of the birr to the U.S. dollar. We also define whether foods are perishable or not to indicate whether these are possibly traded.

Finally, the price of a given food item in a given month closely follows the price of the same item in the previous month. We therefore assume that the real price of each food item is associated with its own lagged values. The econometric analyses are conducted using administrative zone-level aggregated data as most factors possibly influencing these price trends are available at this level of aggregation.

4.3.2. Regression methods

In order to assess the strength of association of certain factors with local prices of cereals, nutritious foods and cooking oil and sugar, we use a zonal fixed effects model. Apart from the factors discussed in Section 4.3.1., we include three additional variables in the price equations to test if the real prices of perishable and non-perishable items are differently associated with variables representing international trade and local production. The literature on trade (e.g., Armington, 1969) shows that differential effects should be expected. We categorize kale, bananas, tomatoes, milk and eggs as perishable items. Teff, wheat, maize, field peas, horse beans, onions and beef[53] are non-perishable. Non-perishability reflects the possibility to trade these items across long distances, although in reality it is legally prohibited to export teff.

[51] Note that high productivity areas capture land productivity (yield) for crops and labor productivity for animal source foods. Labor productivity is defined as output divided by the number of farm holders in the area, as there is no data available on actual labor used in production.

[52] The average price is constructed from prices in the 30 districts with the highest average productivity of the food item during the period considered.

[53] Traded not as beef as such, but mainly through livestock.

The real price of a given food item is therefore expressed as:

$$
\begin{aligned}
P_{ijt} = \alpha_{i0} + \sum_{l=0}^{n} \gamma_{ijt-l} P_{ijt-l} + \sum_{l=0}^{n} \beta_{iat-l} P_{iat-l} \\
+ \sum_{l=0}^{n} \beta_{ibt-l} P_{ibt-l} + \sum_{l=0}^{n} \beta_{ibRt-l} P_{ibt-l} * R_{ijt} \\
+ \sum_{l=0}^{n} \beta_{iht-l} P_{iht-l} + \vartheta_i E_t + \vartheta_{iR} E_t * R_{ijt} + \delta_{iF} F_{jt} \\
+ \delta_{iA} A_{jt} + \delta_{iD} D_{jt} + \delta_{iW} W_{jt} + \delta_{iO} O_{ijt} + \delta_{iOR} O_{ijt} \\
* R_{ijt} + \theta_{i1} T + \theta_{i2} M + \theta_{i3} Y + \mu_{ijt}
\end{aligned}
\tag{1}
$$

where P_{ijt} is the real price of item i in market j and month t; P_{ikt} is the real price of i in Addis Ababa (k=a); boundary markets (k=b), and high productivity area markets (k=h). E_t stands for the exchange rate, F_{jt} for fuel prices in market j, A_{jt} for travel time, D_{jt} for population density, W_{jt} represents lagged wage rate, and O_{ijt} the predicted per capita output of item i in j. R_{ijt} represents a dummy variable that takes a value of 1 if an item is perishable and is used as an interaction term with border prices (P_{ibt}), exchange rate (E_t), and per capita output (O_{ijt}). Included in equation (1) is also a time trend (T), and month/seasonality (M) and year (Y) dummy variables. μ_{ijt} is an identically and independently distributed error term. α_{i0}, $\gamma_i, \beta_{ik}, \vartheta_i, \delta_{in}$ and θ_{is} are parameters to be estimated. We select the optimal lag length of local, commercial cluster, border and Addis Ababa prices by running regressions that include 0 to 6 lags of each of the variables. Results in the subsequent tables derive from equations with a superior performance in terms of log-likelihood, the Akaike information criterion (AIC), and the Bayesian information criterion (BIC).

Our empirical analysis estimates the price equations for the three food categories, in addition to the 14 items individually. The first equation is based on three items from the "Grains, roots, and tubers" food group – maize, teff and wheat. These cereals constitute the major staple foods in most parts of the country and are among the foods with the highest share in total per capita consumption expenditure.[54] The second equation combines the nine food items considered nutritious (field peas, horse beans, milk, eggs, beef, kale, onion, bananas and tomatoes) but are often consumed in small quantities by Ethiopian households. These items saw a marked increase in prices over the period studied, as shown in Figures 2 and 3. The third set of equations combine cooking

[54] In 2011, the average per capita consumption spending on maize was highest out of the145 items in HCES dataset. Spending on teff was second highest, while average spending on wheat ranked fifth. These three cereals accounted for a quarter of the consumption spending of an average individual.

oil and sugar. Being largely manufactured items, zonally disaggregated output data are not available for these food items. The results for the price equations of these three food categories can be found in Table 3.

In addition to estimating the price equations, which indicate the level of association of each factor with local prices of the respective items, we compute the contribution of each factor to observed item price changes between 2005 and 2018. For that purpose we first calculate the short- and long-run elasticities of each factor with respect to prices of the items as done by, for example, Barrett (1997) and Bachewe and Taffesse (2017).[55] The long-run elasticity of real prices with respect to an explanatory variable, for instance Addis Ababa prices, is given by $((\beta_{iat} + \beta_{iat-1})/(1 - \gamma_{ijt-1})) * \frac{\bar{P}_{ia}}{\bar{P}_i}$; where β_{iat} and β_{iat-1} are estimates of the contemporaneous and lagged Addis Ababa market price, respectively; γ_{ijt-1} is the estimate of the lagged dependent variable, and $\bar{P}_{ia}$ and $\bar{P}_i$ are mean values of Addis Ababa market prices and the real price of item i (Bachewe & Taffesse, 2017).[56] The short run elasticity of, for instance, the real exchange rate, is given by: $\vartheta_i * \frac{\bar{E}}{\bar{P}_i}$; where ϑ_i is the estimate of the real exchange rate and $\bar{E}$ is the mean value of the real exchange rate. To calculate the relative contribution of different factors, we then multiply these elasticities by the average annual percentage change of the variable for the short-run, and the sum of the annual percentage changes of the variable for the long-run. While the calculated elasticities might be high, the underlying factors might change very slowly. Consequently, certain factors might have had little contribution to price increases or decreases over the period studied. These results will be presented in Table 4.

4.3.3. Results

The results from our fixed effects model can be found in Table 3. Estimates from the 14 item-specific equations have similar implications to the three food category results.[57] Results from these price equations indicate that local demand and production conditions play an important role in the formation of food prices. The estimates of the coefficients for one time period lagged local retail prices vary between 0.58 and 0.68 for the three equations (Table 3). This indicates the persistence of past prices for current price formation, especially as

[55] Short-run elasticities implicate the immediate effects whereas long-run elasticities indicate effects persistent over a certain time period/several lagged periods. The terms short- and long-run are kept for simplification purposes.

[56] Note that all lags of the respective variables are used in the calculation of long-run elasticities.

[57] Presented in Table A4, Appendix.

coefficients remain significant, albeit decreasing in magnitude, for time lags of up to three periods.

Local supply of items, measured in terms of predicted output per capita, is, as expected, negatively associated with real prices. However, the coefficients are small and are only significant for nutritious foods. On the other hand, demand measured in terms of population density is positive and highly significant. The coefficients are especially high for cereals and cooking oil and sugar. Quarterly average real wages are also positive and significant, although more so for nutritious foods than cereals, and insignificant and close to zero for cooking oils and sugar.

Food prices are also associated with prices in Addis Ababa and in highly productive commercial clusters. The commercial cluster price coefficient is the highest (after the lagged dependent variable) for cereals and nutritious items (Table 3). An increase in prices in areas with the highest land and labor productivity is likely to push up local prices for these foods. The coefficient for Addis Ababa prices is second highest for cooking oils and sugar and third highest for cereals and nutritious foods.[58]

International markets also highly influence local food prices. The coefficient for primary boundary price is however higher than that for real exchange rates for all food groups. This indicates a relatively higher influence of cross-border trade than international trade at a larger scale. Related, the perishability of a food item also shows a differential price formation, as expected a priori. The interaction term between per capita output and the perishable dummy variable indicates that local supply conditions influence perishable items more than it does non-perishable items. Conversely, the positive estimate of real exchange rate and negative estimate of its interaction term with a perishable dummy indicates the more important association of local prices of non-perishables with international prices. Moreover, the estimates of border prices and its interaction with a perishable dummy variable, which are positive and negative, respectively, both contemporaneously and summed across the different lags, indicate that local prices of non-perishable items are influenced more by prices in neighboring countries. Indeed, estimates of the elasticities (Table A5) and contribution of the factors (Table 4) are not statistically significant for perishable items.

Finally, transaction costs matter much less for local price formation. The estimate of mean travel time, a variable intended to gauge the effect of connectedness on local prices, is negative and significant in the price equation for cereals, positive and significant for cooking oils and sugar, and insignificant for nutritious foods (Table 3). The coefficient of fuel prices indicates that higher

[58] This is line with findings from Baffes et al. (2017) in Tanzania where they show the large influence of the city of Nairobi in neighbouring Kenya on local maize prices.

transportation costs are associated with higher prices of nutritious foods, cooking oils and sugar. Cereal prices do not seem to be greatly affected by fuel prices, with an insignificant coefficient close to zero.

Table 4 presents the relative contribution of these different factors on the local price of cereals, nutritious foods, and cooking oil and sugar over the period studied.[59] The results in Table 4 show the importance of international trade in local price formation. Real exchange rate changes have contributed in an important way to keeping local food prices low. This is slightly more so for cereals than nutritious foods and cooking oils and sugar, and especially the case for non-perishable items. Border price increases are more important for nutritious foods with a long-run contribution of 0.14 for non-perishables and 0.05 for perishables. This high influence of border prices is likely linked to significant international trade for a number of these nutritious commodities (as seen in the important export of livestock products and import of some vegetables, such as onions, and powdered milk into Ethiopia). These international trade relations are a seemingly scarcer occurrence for cereals, possibly partly due to a cereal export ban that has been in vogue for most of the period studied. During this period, we have also seen important price changes in international markets for some of these nutritious products (Abegaz et al., 2018), explaining the relatively high contribution of international trade in local price changes.

Apart from cross-border trade, we find that the price of nutritious foods has been significantly impacted by changes in the commercial cluster price. This coefficient is also high, especially in the long-run with a contribution of 0.21, compared to a short-run contribution of 0.01. These commercial clusters are also important for the price formation of cereals, with a long-run contribution of 0.18. These results suggest that stimulating production in regions with a comparative advantage in the production of particular foods is therefore important if one wants to ensure low local food prices.

Local production measured by per capita output also affects nutritious food prices, but only by a small margin in the long-run, a possible indication of integrated agricultural markets in Ethiopia that are therefore less affected by local supply conditions (Minten et al., 2014). Local prices of nutritious foods have also shown important increases due to increasing local urban demand and a more urbanized Ethiopia (Schmidt et al., 2018), as seen by the large influence of the Addis Ababa prices. This is likely driven by increasing incomes in urban areas (World Bank, 2014; 2019) and high-income elasticities for these nutritional foods (Tafere et al., 2010; Worku et al., 2017; Abegaz et al., 2018), thereby pulling prices up in the rest of the country.

[59] Estimates of short-run and long-run elasticities of real retail prices can be found in Table A5, Appendix.

Conversely, population density has the most impact on cereal and cooking oil and sugar prices. Real wage rates of unskilled laborers have influenced the price of cereals and nutritious items over the period studied, indicating the importance of changing incomes and demand in price movements. However, these wages influenced cereal prices slightly more, indicating that such cereal products are more consumed across the board than the nutritious foods that are relatively less consumed by poorer people (Worku et al., 2017). Cooking oil and sugar prices are mostly influenced by Addis Ababa prices and population density, indicating the influence of government subsidies and price caps. Lastly, changes in transaction costs, despite large investments in road infrastructure, have mattered less over the period studied.

4.4 Conclusion and Implications

We study the price evolution of different food groups in Ethiopia from 2005 to 2018, and find that the price of all food groups rich in macro- and micronutrients increased substantially in real terms. These price increases are especially prominent for vitamin A-rich fruit and vegetables, and meat. At the same time, the real price of food groups that are associated with overweight and obesity (oils, fats and sugar) decreased during this time period. These trends confirm the increasing cost of healthy diets seen in emerging and developed economies in recent years. In developing countries, this entails a worsening access to the recommended EAT-Lancet diet across time, especially as the price of food is critically important in the food consumption decisions of low-income households, evident in consistently high estimates of food price elasticities of consumption.[60] Our findings further illustrate that increasing urban demand, production in commercial clusters, and international trade have been particularly important for the price formation of nutritious foods over the period studied.

The Ethiopian government has a good track record with respect to the improvement of cereal production within the country in the last decade. This improvement has been driven by a focus on modernizing the agricultural sector and increased adoption of modern technologies (Bachewe et al., 2018a). It has been shown that increased productivity and production in the cereal sector has brought about considerable improvements in poverty alleviation and in calorie intake (World Bank, 2014). However, such a transformation has not been noted

[60] For example, Tafere et al. (2010) used variation in prices in Ethiopia to study to what extent consumption patterns change with changing prices, based on national consumption survey data. They estimated that price elasticities of most food items were close to -1.0 suggesting that a 10 percent increase in prices is associated with a 10 percent decrease in consumption.

for the consumption of high-value nutritious foods (Bachewe et al., 2018b). As the Ethiopian economy continues to transform, high-value crops, such as fruits, vegetables and animal-source foods, are critical to improving the quality of diets. However, current price trends for these foods will limit their accessibility to the poor.[61]

To reduce price levels, improve dietary quality and ultimately impact nutritional and health outcomes in the country, more investments and attention to the production systems for 'high-value' foods in the crop and livestock subsectors are needed. Our results suggest that efforts should focus on production in commercial clusters since price rises there make an important contribution to local food price rises overall. Such commercial clusters might therefore need more attention in research, and in the policy debate.[62] This is increasingly being realized as seen in recent agricultural development strategies implemented in the country (Diriba & Man, 2019) and elsewhere (Zhang & Hu, 2014). Attention to production is important as efforts to achieve improvements in nutritional outcomes in Ethiopia have mostly focused on improving nutrition knowledge (dietary culture) through behavioral change communication. While important and successful (e.g., Abebe et al., 2016; Kim et al., 2016), improving access to and achieving low prices for these nutritious foods also has an important role to play as part of multi-sectoral efforts to improve nutritional outcomes.

Trade policies also play a role in improving affordability. Border country prices matter especially for nutritious foods and exchange rate changes are found to influence the price of all food items given direct as well as indirect effects through the costs of intermediary inputs, such as chemical fertilizers, agro-chemicals, hybrids seeds, and improved feed ingredients. Finally, government intervention and production subsidies for foods such as oils and sugar should be reduced, so that the price of these foods reflects their true costs.

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[61] As noted in other growing economies, the relative importance of cereals in total food expenditures is already decreasing in Ethiopia. We are beginning to see a shift towards more preferred, but also more expensive foods, including animal-source foods (Worku et al., 2017).

[62] Minten et al. (2020) for example illustrate the importance of a Central Rift Valley cluster for horticultural products in the country.

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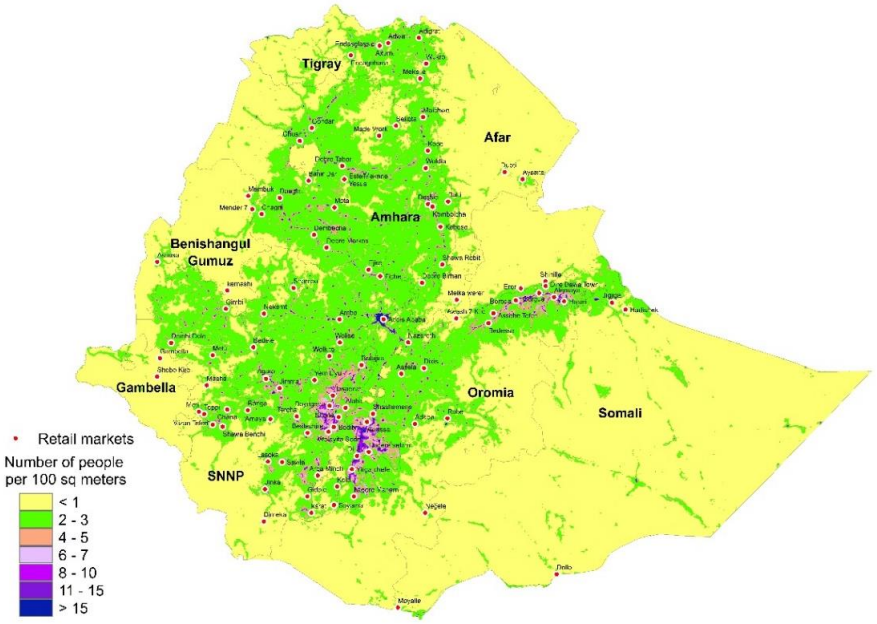
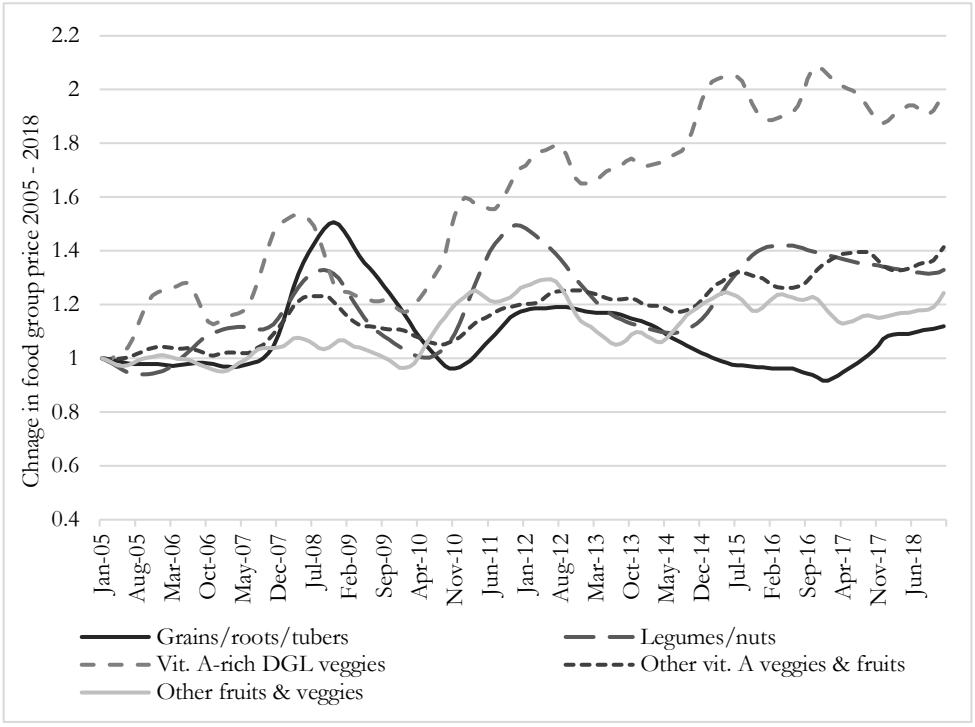
4.6 Figures

Figure 1 | Zones covered by CSA retail price data



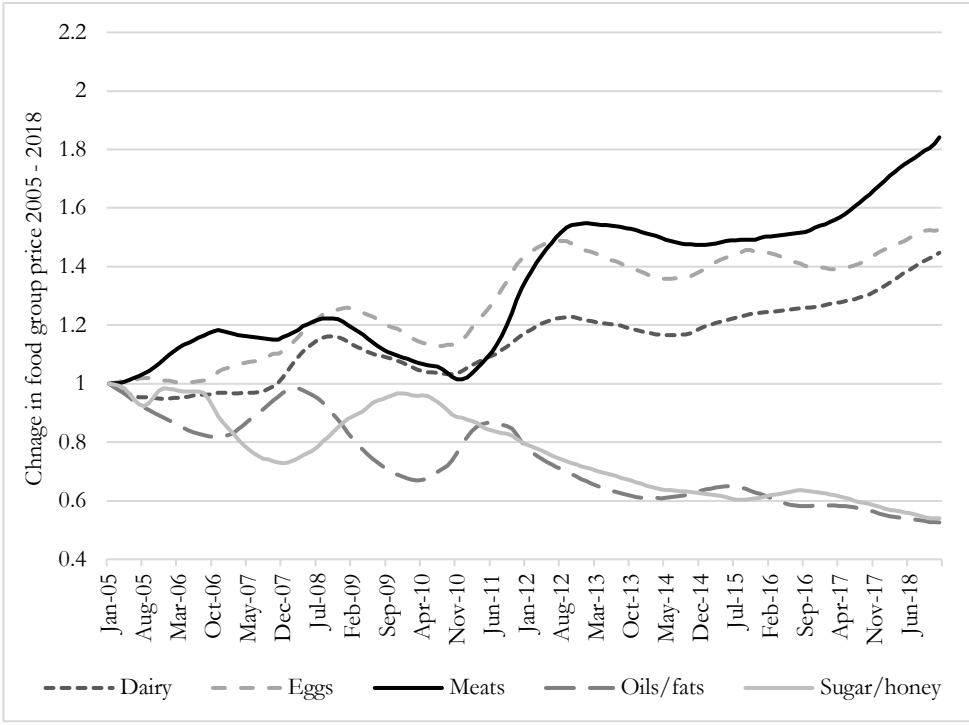
Source: Central Statistical Agency, Ethiopia

Figure 2 | Monthly real consumer price trends of plant-based foods in Ethiopia, 2005 - 2018



Source: Consumer Price Survey (CPS), Household and Consumption Expenditures Survey (HCES)
Note: Smoothed prices using a 12-month centered moving average (MA)

Figure 3 | Monthly real consumer price trends of animal-source foods, oils and fats, and sweeteners in Ethiopia, 2005 - 2018



Source: Consumer Price Survey (CPS), Household and Consumption Expenditures Survey (HCES)

Note: Smoothed prices using a 12-month centered moving average (MA)

4.7 Tables

Table 1 | Descriptive statistics for the ten food groups used in the analysis of price trends

Food group	Items in HCES consumption data, number	Items with retail price data from the Consumer Price Survey, number	Share of total weight of items with price data, %
Grains, roots and tubers	70	34	76.3
Legumes and nuts	52	28	83.9
Dairy products (milk, yogurt, cheese)	9	5	72.9
Eggs	2	1	94.7
Flesh foods and others/small animal protein	15	7	97.1
Vitamin A dark green leafy vegetables	4	3	97.6
Other Vitamin A rich vegetables and fruits	8	5	83.3
Other fruits and vegetables	34	16	90.4
Oils and fats	11	5	86.4
Sugar and honey	6	2	58.3
All food groups	211	106	83.3

Source: Consumer Price Survey (CPS), Household and Consumption Expenditures Survey (HCES)

Note: Column 4 shows the share of each item in the food group's total per capita quantity consumed. This is portrayed by their weight in each food group reported to be consumed in the HCES dataset and for which prices are available in the Consumer Price Survey dataset.

Table 2 | Evolution of annual median retail prices, by food group, percentage total change in real prices between 2005 and 2018

	2005	2012	2018	Total change (%)
Grains, roots and tubers	6.8	8.5	7.2	5.6
Legumes and nuts	13.2	19.6	18.1	37.5
Dairy products	10.6	13.3	15.0	40.9
Eggs	15.3	23.0	23.3	52.1
Flesh foods and others/small animal protein	48.7	70.8	82.6	69.5
Vitamin A dark green leafy vegetables	2.7	4.2	4.6	73.6
Other Vitamin A rich vegetables and fruits	3.9	4.5	4.8	22.7
Other fruits and vegetables	8.3	10.9	10.0	20.8
Oils and fats	40.3	30.0	23.7	-41.0
Sugar and honey	21.8	16.1	11.2	-48.8

Source: Consumer Price Survey
Note: Percentage change computed using average annual real prices of items in 2018 and 2005

Table 3 | Contributing factors to food prices, mean equation

Variables	Cereals		Nutritious foods		Cooking oil and sugar	
	Coef.	SE	Coef.	SE	Coef.	SE
Local retail price (t-1)	0.643***	0.006	0.583***	0.004	0.676***	0.007
Local retail price (t-2)	0.082***	0.006	0.067***	0.004	0.091***	0.009
Local retail price (t-3)					0.086***	0.007
Commercial cluster price	0.413***	0.012	0.393***	0.007		
Commercial cluster price (t-1)	-0.244***	0.015	-0.114***	0.009		
Commercial cluster price (t-2)	-0.027**	0.012	-0.110***	0.007		
Addis retail price	0.289***	0.016	0.227***	0.007	0.379***	0.015
Addis retail price (t-1)	-0.236***	0.018	-0.127***	0.008	-0.087***	0.021
Addis retail price (t-2)	-0.047***	0.015	-0.041***	0.007	-0.196***	0.022
Addis retail price (t-3)					-0.001	0.016
Primary boundary	0.179***	0.012	0.261***	0.013	0.312***	0.013
Primary boundary (t-1)	0.002	0.012	-0.153***	0.017	-0.068***	0.017
Primary boundary (t-2)	-0.063***	0.011	-0.008	0.013	-0.131***	0.017
Primary boundary (t-3)					-0.078***	0.013
Mean travel time	-0.007**	0.003	0.006	0.007	0.010***	0.003
Fuel price (birr/liter)	-0.002	0.003	0.009*	0.005	0.011**	0.005
Population per crop area (number/km2)	0.168***	0.031	0.002**	0.001	0.136***	0.032
Per capita output (kgs)	-0.005	0.004	-0.005***	0.002		
Real wages (quarterly average)	0.007*	0.004	0.013***	0.004	-0.004	0.004
Real monthly exchange rate (birr/USD)	0.020**	0.008	0.030***	0.009	0.017**	0.008
Interaction of primary boundary and perishable dummy			-0.192***	0.015		
Interaction primary boundary (t-1) and perishable dummy			0.164***	0.019		
Interaction primary boundary (t-2) and perishable dummy			-0.014	0.014		
Interaction of per capita output and perishable dummy			0.004**	0.002		
Interaction of exchange rate and perishable dummy			-0.019***	0.007		
Time trend (monthly)	-0.000***	0.000	0.000**	0.000	-0.000	0.000
Constant	-0.808***	0.147	-0.086**	0.042	-0.632***	0.147
Seasonality (month) dummies	Yes		Yes		Yes	
Year dummies	Yes		Yes		Yes	
sigma_u	0.162		0.100		0.131	
sigma_e	0.080		0.158		0.070	
Log-Likelihood	28,052		30,543		22,559	
Observations	25,206		71,564		18,150	

Table 4 | Contribution of factors to changes in real retail prices, 2005 to 2018

Variables	Cereals				Nutritious foods				Cooking oil and sugar			
	Short-run		Long-run		Short-run		Long-run		Short-run		Long-run	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Commercial cluster price	0.011***	0.000	0.184***	0.010	0.013***	0.000	0.207***	0.007				
Addis Ababa retail price	0.014***	0.001	0.015	0.027	0.009***	0.000	0.092***	0.010	-0.021***	0.001	-0.477***	0.042
Mean travel time	000**	0.000	0.014**	0.007	000	0.000	-0.005	0.005	000***	0.000	-0.013***	0.005
Fuel price	000	0.000	0.009	0.013	000*	0.000	-0.013*	0.007	000**	0.000	-0.026**	0.012
Population density	0.107***	0.020	4.675***	0.862	0.004**	0.002	0.128**	0.059	0.231***	0.054	18.992***	4.416
Wage rate	0.001*	0.001	0.064*	0.037	0.001***	0.000	0.045***	0.015	000	0.000	-0.023	0.025
Border price												
Non-perishable	0.003***	0.000	0.105***	0.010	0.01***	0.000	0.14***	0.010	-0.011***	0.000	-0.11***	0.031
Perishable					0.001***	0.000	0.046***	0.006				
Per capita output												
Non-perishable	-0.001	0.001	-0.067	0.052	000***	0.000	-0.005***	0.002				
Perishable					000	0.000	-0.007	0.012				
Real exchange rate												
Non-perishable	-0.002***	0.001	-0.11***	0.043	-0.001***	0.000	-0.038***	0.012	-0.001**	0.000	-0.058**	0.029
Perishable					-0.001	0.001	-0.035	0.030				

Note: Short-run contributions are calculated by the short run elasticity*average annual percentage change; long-run contributions are calculated by the long-run elasticity*sum of annual percentage change in factor.

4.8 Appendix

Figure A1 | General, food and non-food CPI from 2005-2018

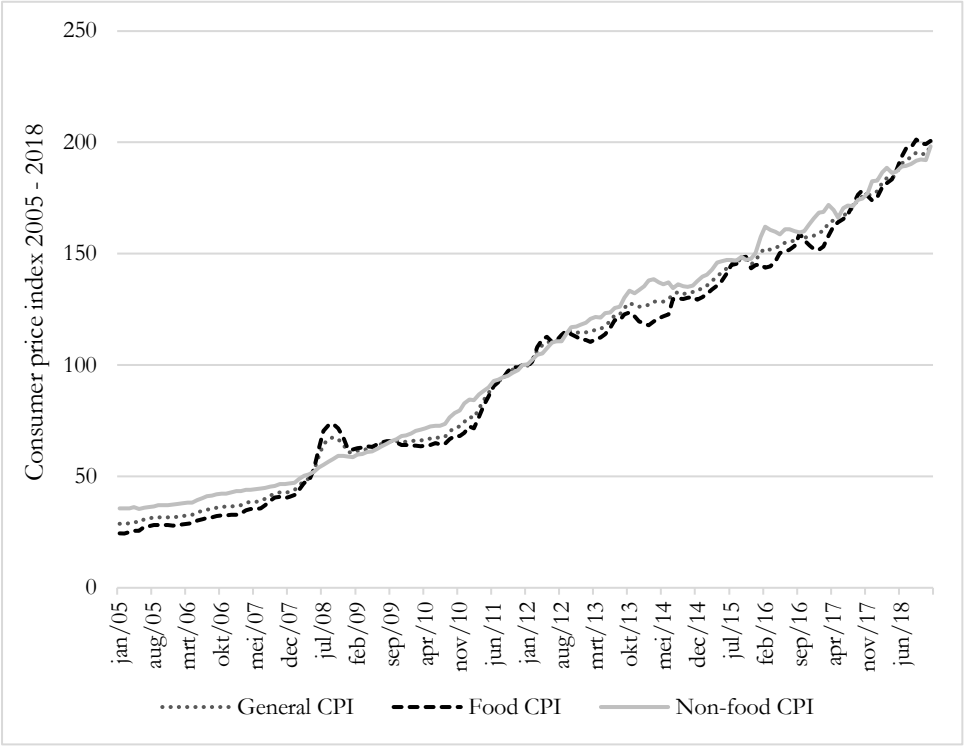


Table A1 | Average item weight in total per capita consumption per food group

Food group	Item	Average weight of item in per capita consumption of all items in food group
Grains, roots and tubers	teff white, whole grain	0.3998808
	teff white, flour	3.954278
	teff mixed, whole grain	0.1704072
	teff mixed, flour	5.58742
	teff black, whole grain	0.2493253
	teff black, flour	4.147771
	wheat white, whole grain	0.5678507
	wheat white, flour	4.878266
	wheat mixed, whole grain	0.0047864
	wheat mixed, flour	0.1974353
	wheat black, whole grain	0.5635229
	barley white, whole grain	0.339523
	barley white, flour	1.881725
	barley mixed, whole grain	0.0477441
	barley mixed, flour	0.2455576
	barley black, whole grain	0.0727545
	barley, brewery type, whole grain	0.0048511
	emmur wheat (aja), whole grain	0.0106261
	hulled barley(temege), whole grain	0.0383905
	oats (sinar), flour	0.1046628
	African millet, whole grain	0.0003432
	maize, whole grain	3.139315
	maize, flour	15.83972
	sorghum, whole grain	0.6993927
	sorghum, flour	13.08947
	durrah, whole grain	0.1607408
	durrah, flour	0.9549667
	rice	0.8792527
	enjera	2.734859
	sweet potato, raw	2.925092
	indigenous potatoes (boyna, agew or fur	0.0663302
	qocho, raw	11.33035
	bula wet	0.0933919
	fafa/ dube , balanced baby diet	0.2353972
Legumes and nuts	faba bean , whole grain	6.081155
	faba beans, flour (shiro)	7.495331
	faba beans, split (kik)	7.000622
	chick peas, whole grain	1.436844
	chick peas, flour (shiro)	0.8155403
	chick peas, split (kik)	1.097966
	field peas, whole grain	1.913622
	field peas, flour (shiro)	11.85723
	field peas, split (kik)	6.552458
	soya beans, whole grain	0.2179917
	lentils, whole grain	1.663635
	lentils, split (kik)	7.609811
	haricot / kidney beans, whole grain	14.22321
	grass peas, whole grain	0.0566736

	grass peas, flour (shiro)	5.091564
	grass peas, split (kik)	0.7002538
	mixed pulses, flour (shiro)	4.185286
	fenugreek, whole grain	1.096426
	fenugreek, flour	2.151699
	others n.e.c. , whole grain	0.0028623
	others n.e.c. flour (shiro)	0.01027
	others n.e.c. split (kik)	0.001435
	nigro / niger seed	0.1623196
	linseed (telba)	0.5393193
	sesame	0.174796
	sun-flower	0.3445735
	ground nuts	0.5174471
	rape seed	0.1200246
Dairy products	cow milk, raw	46.92625
	camel milk, raw	0.6063444
	sour milk / cottege yoghurt	8.502581
	cottage cheese	13.4821
	powdered milk	0.7799609
Eggs	eggs, indigenous	94.71091
Flesh foods and other small animal protein	beef	52.64311
	sheep meat	15.20766
	goat meat	15.8538
	camel meat	0.2681266
	chicken	10.85555
	fresh or frozen fish, whole	2.55315
	sardines & tuna, canned fish	0.066848
Vitamin A dark green leafy vegetables	Ethiopian kale	85.02166
	lettuce	4.689843
	spinach	5.519367
Other Vitamin A rich vegetables and fruits	papaya	8.265614
	mango	12.56082
	leek	8.502604
	pumpkin	40.31216
	carrot	13.74682
Other fruits and vegetables	banana	9.730757
	orange / mandarin	1.838074
	lemon	0.3804425
	avocado	3.322787
	prickly pear (beles)	1.457889
	head cabbage	8.944674
	cauliflower & swiss chard	0.9013052
	pepper green	5.607835
	beet root	1.600958
	tomato	16.02156
	onions	33.83642
	garlic	4.226269
	others n.e.c.	0.03294
	red pepper whole	0.1549226
	ginger	1.971733
	canned tomato, sauce	0.3640965

Oil/fats	butter, unspiced & non- refined	4.662086
	edible oil, local	16.77262
	edible oil , imported	64.56421
	edible vegetable butter, imported	0.4853684
	others n.e.c.	0.0026566
Sugar/honey	sugar	54.8396
	honey, natural	2.203919

Table A2 | First-stage regressions for crops

Variables	Maize	Teff	Wheat	Horse beans	Field peas	Bananas	Kale	Onion	Tomato
	coef (se)	coef (se)	coef (se)	coef (se)	coef (se)	coef (se)	coef (se)	coef (se)	coef (se)
Total rainfall during cropping season	1.546	0.666	-6.305***	-3.786	-1.204	2.845	0.007	-8.545***	-6.918
	(1.146)	(1.903)	(2.181)	(2.941)	(2.813)	(2.651)	(3.165)	(2.943)	(4.745)
Total rainfall during cropping season squared	-0.130	-0.053	0.467***	0.231	0.072	-0.226	-0.042	0.638***	0.552
	(0.085)	(0.138)	(0.162)	(0.212)	(0.203)	(0.190)	(0.228)	(0.214)	(0.360)
Number of oxen	0.600***	0.620***	1.097***	0.843***	0.971***	0.708***	0.783***	0.854***	0.553**
	(0.114)	(0.096)	(0.169)	(0.175)	(0.188)	(0.171)	(0.112)	(0.242)	(0.253)
Mean travel time	0.242	0.225	0.379*	0.203	0.313	0.170	-0.121	1.037***	-0.418
	(0.155)	(0.168)	(0.225)	(0.248)	(0.229)	(0.465)	(0.260)	(0.397)	(0.514)
Administrative zone dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-2.020	-0.119	10.408	11.211	-2.891	-17.646*	-7.171	20.146**	22.187
	(3.964)	(6.726)	(8.446)	(10.383)	(9.870)	(9.963)	(11.517)	(10.223)	(15.750)
R2	0.932	0.951	0.944	0.937	0.884	0.876	0.914	0.763	0.661
Adjusted R2	0.926	0.946	0.937	0.931	0.872	0.863	0.904	0.734	0.609
Log-Likelihood	-662.48	-567.32	-862.35	-691.88	-846.08	-1,099.54	-882.41	-1,236.10	-1,231.99
Observations	953	827	821	768	770	799	737	751	641

Note: Estimates with superscripts ***, **, and * are significant at 1%, 5%, and 10% levels of significance.

Table A3 | First-stage regressions for animal products

Variables	Beef	Milk	Eggs
	coef (se)	coef (se)	coef (se)
Number of cattle used in production (log)	1.073***	1.068***	
	(0.031)	(0.011)	
Cattle deaths due to disease or other (% of stock)	0.212***	0.014	
	(0.031)	(0.027)	
Mean travel time	0.046	0.021	-0.194***
	(0.060)	(0.020)	(0.018)
Number of egg-lying chicken			1.004***
			(0.009)
Poultry deaths due to disease or other (% of stock)			-0.035
			(0.048)
Region dummy	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes
Constant	-6.527***	-3.315***	-4.196***
	(0.439)	(0.162)	(0.241)
R2	0.976	0.963	0.971
Adjusted R2	0.974	0.962	0.970
Log-Likelihood	27.28	-153.64	-152.75
Observations	965	966	963

Note: Estimates with superscripts ***, **, and * are significant at 1%, 5%, and 10% levels of significance.

Table A4 | Contributing factors to food prices, item specific equations

Panel A: Cereals, cooking oil and sugar

	Maize	Wheat	Teff	Oil	Sugar
Local retail price (t-1)	0.649***	0.631***	0.603***	0.714***	0.630***
Local retail price (t-2)	0.063***	0.132***	0.115***	0.097***	0.092***
Local retail price (t-3)				0.044***	0.126***
Regional markets price	0.435***	0.341***	0.311***		
Commercial cluster price (t-1)	-0.349***	-0.150***	-0.191***		
Commercial cluster price (t-2)	0.002	-0.053***	0.034		
Addis retail price	0.282***	0.383***	0.460***	0.214***	0.513***
Addis retail price (t-1)	-0.196***	-0.318***	-0.289***	0.138***	-0.201***
Addis retail price (t-2)	-0.106***	-0.047	-0.104***	-0.118***	-0.215***
Addis retail price (t-3)				-0.040	0.015
Primary boundary	0.157***	0.207***	0.273***	0.271***	0.288***
Primary boundary (t-1)	0.078***	-0.069***	-0.160***	-0.094***	-0.065***
Primary boundary (t-2)	-0.021	-0.068***	-0.043*	-0.136***	-0.069***
Primary boundary (t-3)				-0.085***	-0.092***
Mean travel time	-0.011	-0.000	-0.006	0.013**	0.008*
Fuel price (birr/liter)	-0.009	-0.007	0.012**	0.030***	0.003
Population per crop area (number/km2)	-0.006**	-0.001	0.092**	0.157***	0.126***
Per capita output (kgs)	0.015	-0.008	-0.015*		
Real wages (quarterly average)	0.019**	0.006	-0.003	0.001	-0.008*
Real monthly exchange rate (birr/USD)	0.031*	-0.003	0.032***	0.037**	0.005
Time trend (monthly)	-0.000	-0.000	0.000	0.000**	-0.000
Constant	-0.141*	0.052	-0.516***	-0.954***	-0.624***
sigma_u	0.055	0.019	0.096	0.151	0.124
sigma_e	0.104	0.068	0.054	0.073	0.066
Log-Likelihood	7,686	10,355	12,137	10,932	11,812
Observations	9,024	8,096	8,086	9,075	9,075

Panel B: Legumes, fruit and vegetables

	Horse beans	Field peas	Bana-nas	Kale	Onion	Toma-toes
Local retail price (t-1)	0.526***	0.663***	0.513***	0.580***	0.532***	0.557***
Local retail price (t-2)	0.145***	0.067***	0.217***	0.014	0.018	0.003
Regional markets price	0.387***	0.264***	0.287***	0.259***	0.404***	0.350***
Commercial cluster price (t-1)	-0.092***	-0.054**	-0.094**	-0.058*	-0.172***	-0.169***
Commercial cluster price (t-2)	-0.094***	-0.116***	-0.022	-0.015	-0.023	-0.053*
Addis retail price	0.213***	0.083***	0.218***	0.186***	0.223***	0.197***
Addis retail price (t-1)	-0.096***	-0.053*	-0.010	-0.141***	-0.069***	-0.063***
Addis retail price (t-2)	-0.052*	-0.076***	-0.189***	-0.092**	-0.054***	0.007
Primary boundary	0.136***	0.248***	0.043	0.037	0.325***	0.117***
Primary boundary (t-1)	-0.146***	-0.105***	-0.056*	0.065**	-0.142***	-0.029
Primary boundary (t-2)	0.017	0.002	0.007	-0.066**	-0.031	0.038
Mean travel time	0.006	0.040***	0.071***	-0.003	-0.033	-0.003
Fuel price (birr/liter)	0.028***	0.054***	-0.003	-0.139***	0.019	0.022
Population per crop area (number/km2)	0.005***	0.002	0.000	-0.003	0.003**	0.003
Per capita output (kgs)	0.012*	0.023***	0.001	0.022***	-0.010***	-0.006
Real wages (quarterly average)	0.014*	0.015**	-0.004	0.040	0.001	-0.031
Real monthly exchange rate (birr/USD)	0.042**	0.035**	-0.001	0.112	-0.054	0.017
Time trend (monthly)	0.000**	0.001***	0.001**	0.001	-0.000	0.000
Constant	-0.238**	-0.266***	0.067	0.249	0.100	-0.019
sigma_u	0.050	0.071	0.119	0.171	0.056	0.078
sigma_e	0.091	0.074	0.166	0.309	0.160	0.225
Log-Likelihood	7,388	9,135	3,054	-1,713	3,216	513
Observations	7,552	7,658	7,944	7,134	7,646	6,240

Panel C: Animal products

	Beef	Milk	Egg
Local retail price (t-1)	0.687***	0.645***	0.431***
Local retail price (t-2)	0.149***	0.175***	0.164***
Regional markets price	0.064***	0.111***	0.254***
Commercial cluster price (t-1)	-0.030	-0.139***	-0.166***
Commercial cluster price (t-2)	-0.015	0.003	0.027
Addis retail price	0.454***	0.013	0.419***
Addis retail price (t-1)	-0.160***	0.069*	-0.261***
Addis retail price (t-2)	-0.255***	-0.021	-0.000
Primary boundary	0.222***	0.076***	0.126***
Primary boundary (t-1)	-0.141***	-0.028	-0.018
Primary boundary (t-2)	-0.036**	-0.030	-0.002
Mean travel time	-0.012	0.005	-0.012
Fuel price (birr/liter)	0.014**	0.019**	0.038***
Population per crop area (number/km2)	-0.053	0.123**	-0.165***
Per capita output (kgs)	-0.002	-0.005	-0.000
Real wages (quarterly average)	0.008	0.017**	0.028***
Real monthly exchange rate (birr/USD)	0.009	0.036**	0.087***
Time trend (monthly)	0.000**	0.000	0.001***
Constant	0.398*	-0.504*	0.307
sigma_u	0.059	0.120	0.160
sigma_e	0.070	0.096	0.095
Log-Likelihood	11,405	8,440	8,594
Observations	9,130	9,130	9,130

Table A5 | Estimates of short-run and long-run elasticities of real retail prices[63]

Variables	Cereals				Nutritious foods				Cooking oil and sugar			
	Short-run		Long-run		Short-run		Long-run		Short-run		Long-run	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Commercial cluster price	0.388***	0.011	0.483***	0.027	0.383***	0.007	0.473***	0.015				
Addis Ababa retail price	0.337***	0.018	0.028	0.050	0.257***	0.007	0.191***	0.020	0.345***	0.013	0.594***	0.052
Mean travel time	-0.004**	0.002	-0.015**	0.007	0.002	0.002	0.005	0.005	0.002***	0.001	0.014***	0.005
Fuel price	-0.005	0.007	-0.018	0.027	0.009*	0.005	0.026*	0.013	0.008**	0.004	0.055**	0.026
Population density	3.454***	0.637	12.582***	2.320	0.121**	0.055	0.345**	0.158	7.458***	1.752	51.118***	11.886
Wage rate	0.029*	0.016	0.104*	0.059	0.026***	0.009	0.074***	0.025	-0.005	0.006	-0.037	0.040
Border price												
Non-perishable	0.203***	0.013	0.487***	0.045	0.287***	0.014	0.313***	0.022	0.321***	0.013	0.244***	0.069
Perishable					0.086***	0.011	0.206***	0.027				
Per capita output												
Non-perishable	-0.033	0.025	-0.119	0.093	-0.001***	0.000	-0.004***	0.001				
Perishable					-0.001	0.002	-0.003	0.005				
Real exchange rate												
Non-perishable	0.047***	0.018	0.171***	0.067	0.021***	0.007	0.059***	0.019	0.014**	0.007	0.094**	0.046
Perishable					0.019	0.016	0.054	0.046				

[63] The long-run and short-run elasticities of real food prices with respect to the three independent variables that are interacted with the perishable dummy variable also involve the estimate of the interaction term in the nutritious items' equation. Accordingly, the long-run elasticity of real prices with respect to e.g. the border prices of perishable items is given by $((\beta_{ibt} + \beta_{ibt-1} + \beta_{ibt-2} + \beta_{ibt-3} + \rho_{it} + \rho_{it-1} + \rho_{it-2} + \rho_{it-3})/(1-\gamma_i)) * \frac{\bar{P}_{ib}}{\bar{P}_i}$; where β_{ibt-k}, are estimates of contemporaneous (k=0) and 1, 2, 3 month lagged (k=1, 2, 3) border market price and ρ_{it-k} are estimates of the interaction of perishable dummy with the respective four variables. $\bar{P}_{ib}$ is the mean value of border market prices. In contrast, the long-run elasticity of real prices with respect to border prices of non-perishable items excludes estimates of the interaction terms from the sum in the first parentheses. Similarly, the short-run elasticity of real price with respect to e.g. the per capita output of non-perishable items is given by $(\delta_{iO} + \varphi_i) * \frac{\bar{O}_i}{\bar{P}_i}$; where δ_{iO} is the estimate of per capita output; $\bar{O}_i$ is mean per capita output of item i; and φ_i is the estimate of the interaction of per capita output and perishable dummy.

Chapter 5. Measuring macro- and micronutrient consumption in multi-purpose surveys: Evidence from a survey experiment in Tanzania*

5.1 Introduction

Nutritious diets are important for human health. Health is not only a prime development outcome, but also feeds into many, if not most, other dimensions of well-being. The development community used to be primarily concerned with hunger, focusing on how many people had insufficient dietary energy and considering what the best ways were to ensure adequate calorie consumption. With economic development came a 'nutrition transition' adding, alongside hunger, excess calories and nutrient deficiencies to the list of public health concerns in developing countries.[64] The World Health Organisation estimates that one out of three people in the world suffer from either wasting, stunting, vitamin and mineral deficiency, being overweight or obese, or from a diet-related non-communicable disease (WHO, 2017).

At the same time that increased attention has been directed to the nutrition transition, researchers and policy-makers have also gained a deeper appreciation of the physiological connections between nutritional consumption and in-utero development, children's cognitive and physical development and adult health. Consequently, we now have a reasonable idea of what a healthy and environmentally sustainable diet may look like, although uncertainty remains on how to make it universally available and affordable (Willett et al., 2019; Hirvonen et al., 2019). Policies that aim to improve nutrition require an understanding of how incomes, prices and preferences come together to determine the nutritional choices that consumers make. Understanding such choices lies at the heart of what economics is about and it is therefore no surprise that there

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64 See, for example, Ramakrishnan (2002), Black et al. (2013), Forouzanfar et al. (2013), Pingali and Sunder (2017), Popkin (2017), Perez-Escamilla et al. (2018) and Imamura et al. (2015).

is increased interest to move beyond calories towards a 'new economics of nutrition' (Finaret and Masters, 2019).

Studying the economics of nutrition is complex as it requires us to understand the consumption of a large number of different macro- and micronutrients that together with individual and environmental circumstances will determine nutritional status. This means moving beyond measuring the effects of nutrient deficiencies (which is what we do when we collect anthropometric data or take haemoglobin test kits to the field) to getting a more complete picture of nutritional consumption, broken down into specific food items and their respective macro- and micronutrient contents. Moreover, these detailed nutrition data should, preferably, be part of a survey that collects additional relevant socio-economic information as this information is needed to model the determinants of consumption.

Recognising that data collection budgets are finite, one promising avenue would be to assess nutrient consumption through on-going initiatives. A good starting place would be the food consumption modules included in household consumption and expenditure surveys (Zezza et al., 2017), which are conducted at national level across the developing world. They are repeated over time and often include a wide range of other socio-economic information on households and individuals, such as health, education, agriculture and so forth. These modules were not designed to measure nutritional content, being primarily included to measure the monetary value of consumption from which poverty and inequality indicators can be derived. However, given that food constitutes such a large portion of the consumption expenditures of poor people, such surveys will tend to collect a wealth of food consumption data. For example, food consumption is typically recorded from various sources (whether purchased, home produced or given) and information on quantities consumed of individual food items is often available, which can be linked to their nutritional content. In short, household consumption and expenditure surveys (HCES) are ubiquitous and hold the potential to reveal something about the nutritional content of what people are eating (De Haen et al., 2011; Fongar et al., 2019).

One concern is that the design of these surveys varies in several dimensions and there is little guidance on the best data collection method (Fiedler et al., 2008; Carletto et al., 2013). This design variation raises concerns about the analytical consequences of using different survey methods and about the potential fragility of results dependant on comparisons across surveys that use different methods (Beegle et al., 2012; Gibson et al., 2014; De Weerdt et al., 2016; Friedman et al., 2017). Survey methods differ across countries and some countries also change their survey method, which introduces differences over time. For

example, recent FAO and World Bank (2018) guidelines for food data collection in household surveys recommend using a 7-day recall, necessitating a switch in survey method for many countries.

To provide evidence on these questions, we randomly assigned six different modules to measure the quantity of food consumption across Tanzania, three using diaries and three using recall methods. The modules differ by survey observation period, by length of the food recall list, by type of survey reporter (individual reporting or a single reporter per household) and by frequency of interviewer visits. Some earlier research using food consumption data from this experiment presents results on the basis of 58 food groups (De Weerdt et al., 2016; Friedman et al., 2017). However, these studies only consider the impact of survey design on total calories or on the total value of food consumption.

In contrast to previous studies we provide three innovations. First, we have access to detailed descriptions of the actual foods reported in diaries by the survey respondents. This allows us to disaggregate more finely, using 99 individual food items that we link to Tanzanian food composition tables (Lukmanji et al., 2008). Second, with this link we are able to assign macro- and micronutrient information to all consumed items. From these data we calculate the percentage consumed relative to the dietary reference intakes of calories, protein, fats, sugars, fiber and 16 micronutrients, taking into account the age and gender composition of each household. Our third innovation is to use linear programming to calculate the regional cost of least cost diets that meet all of the macro- and micronutrient recommendations. These go beyond the more typically used cost-of-basic-needs food poverty lines. Our motivation for these cost calculations is that survey design not only affects the measurement of how apparent consumption compares to recommendations, but also affects calculated costs of potential public transfers that are designed such that recipients could afford minimally adequate diets.

Our analysis uses data from the highly supervised individual diaries (based on daily checking on respondents) as our 'true' measure of the inflows and outflows of food into the household. When comparing the data from the other five survey modules (household diaries and recall modules) to our 'true' food consumption module, the apparent consumption of total and animal-sourced protein, cholesterol and fiber are more sensitive to the use of different consumption modules than is the case for calorie consumption. Thus, previous findings that focus solely on calories, such as De Weerdt et al. (2016), may understate the lack of robustness of nutritional indicators to the variation in survey methods. We also find that using household diaries rather than the highly

monitored individual diaries results in the understatement of vitamin and mineral consumption.

Whilst household diary modules underestimate macronutrient consumption slightly, 14-day recall modules do so more substantially, underestimating calories by 17%, protein by 40%, fat by 27%, and carbohydrate consumption by 11%. Conversely, the 7-day recall module performs similarly to the household diaries, although overestimating the consumption of carbohydrates, sugar and fiber by about 20%. Vitamin and mineral consumption for 7- and 14-day recall modules are also generally underestimated, except for nutrients derived from higher reported cereal consumption. Important mechanisms that may contribute to the degree of mismeasured nutrient consumption, such as respondent's education, household size, wealth (based on an asset index) and whether they live in urban or rural locations, are also discussed.

When exact macro- and micronutrient consumption cannot be measured, food expenditures can be compared to food poverty lines instead. We construct two such lines. First, the minimum cost (MC) diet, derived through linear programming, is calculated per region to account for price differences across Tanzania. Dar es Salaam is the most expensive region in our sample, with a minimum cost macro- and micronutrient-fulfilling diet of 412 TZS per person, per day (equivalent to USD 0.36 per day). The resulting food-poverty prevalence rate varies by survey module. Consistent with the results for understated nutrient consumption, the 14-day recall overestimates the prevalence of extreme food poverty, suggesting that 11% of people in our sample live in households where total food expenditure is below what is needed to buy the minimum cost diet. This is more than twice the rate of extreme food poverty shown by the benchmark individual diary. In contrast, the frequently checked household diary and the 7-day recall perform most closely to the individual diaries at the national level, although with several discrepancies at the regional level.

We then determine how much it would cost to transfer the amount of the shortfall to each household under the food poverty line. Using our benchmarks, the best estimate is USD 51 million per year, with the 7-day recall coming closest with an estimate of USD 69m. The 14-day recall module, by contrast, gives a much more exaggerated annual figure of USD 159m for the same hypothetical programme, working through both an overestimate of the number of people under the MC line and their average shortfall.

Along the same lines, we also calculate a food poverty line based on the typical diet of the poor (specifically, the poorest two quintiles of households) scaled to exactly provide the daily calorie requirement. There is much greater

regional variation in this line than in the one calculated through linear programming. That is because this food poverty line reflects actual consumer choice, while the linear programming exercise of finding the cheapest combination of foods that satisfy dietary reference intakes does not take any taste considerations into account. We see that the food poverty line is two to three times higher than what comes out of the linear programming calculations in all regions. But, the discrepancy is especially large in Dar es Salaam and Pwani, indicating a stronger preference for more expensive macro- and micronutrients in these places. Together, these two sets of calculations suggest a practical implication of the lack of robustness across the different survey designs. Setting possible transfer programs to eliminate food poverty when using some survey designs may produce excessive budgetary requests, which could affect the political feasibility of attempting to eliminate hunger with targeted transfers.

Overall, we find that the 7-day recall is relatively good at predicting average nutrient consumption, as well as providing decent predictions for the prevalence and depth of food poverty. However, the performance of 7-day recalls does seem to depend on household characteristics, so it needs to be used cautiously when studying the correlates of nutrient consumption.

5.2 Data

The data used in this paper come from a survey experiment where eight types of consumption survey modules were randomly assigned across 4000 households in Tanzania, about 500 households per module. Data were collected from September 2007 to August 2008. We use data from six modules as the two remaining modules lack the details needed on food quantities to calculate nutrient content. The experiment was fielded in several regions including Dodoma, Pwani, Dar es Salaam, Shinyanga and Kagera, and covers both urban and rural areas. Randomization was conducted within each of the 168 sampling units ('villages'), with each survey module assigned to three households per village. The randomization was successful according to the balance tests reported in Beegle et al. (2012).

The survey modules differ by observation period, by length of the food consumption list, by type of survey reporter (individual or a single reporter per household) and by intensity of interviewer visits. Three modules use the recall method, where food consumption is recalled by a single respondent on behalf of the household, in a single verbal interview that covers either the last 7 days or the last 14 days. The recall modules also differ in the number of food and drink groups used to prompt the recall, based on either 58 groups or a subset

of 17 important groups. Note that the typical food consumption methods used by nutritionists i.e. the individual 24h recall (Bouis et al., 1992; Bouis, 1994), are not included in this study. HCES data already include food consumption and expenditures, which is why the modules used in these surveys are interesting to dissect.

The other three modules use the diary method, where respondents record daily transactions in open form diaries for a 14 day period. The diary modules are of an acquisition type, adding all products coming into the household through harvests, purchases, gifts and stock reductions as well as subtracting all items not consumed through sales, stock increases and gifts. Food waste and food given to animals are taken into account and guest meals and meals consumed outside of the household are also recorded. The diary modules differ in two ways. First, the reporting is done by either each individual adult (who also reports on behalf of children and others for whom they are responsible and who are incapable of completing the diaries) or at the household level where there is a single diary-keeper for the whole household. Individual level recording entails that each adult member records products they or their charges have brought into the house. These are then stored (so show up as a stock increase) or consumed by the household as a whole. Second, the frequency of interviewer visits differs. Frequent visits entails daily visits by the local assistant and visits every other day by the survey enumerator for the duration of the two-week diary. The infrequent visit treatment entails three visits: to deliver the diary (day one), to pick up the first week diary and drop off the week two diary (day eight), and to pick up the second week diary (day 15).

The personal diaries are taken as our reference category, because these diaries present household consumption most accurately. Diary holders received regular visits from the survey teams and resident enumerators to help them fill in the diaries and to avoid double counting across multiple diaries. During this survey experiment, specific investments were made to ensure the personal diaries could provide a benchmark for analytic comparisons (Beegle et al., 2012).

As the diary modules recorded detailed Swahili descriptions of all foods consumed, we exploited this information to disaggregate the original food groups into 99 food items and groups. This lets us split up important food groups containing multiple types of vegetables or fruit, as well as specific snacks and full meals. In doing so, we are able to link the individually consumed products or meals to their macro- and micronutrient content using the Tanzanian Food Composition tables (Lukmanji et al., 2008). Using the quantities of food consumed, we calculate calorie consumption, as well as macronutrient consumption of protein, animal protein, fat, saturated fat, cholesterol, carbohydrates,

fiber and sugars. Micronutrient consumption was also calculated for vitamins (vitamin A, B1, B2, B3, B6, B9, B12, C and E) and minerals (calcium, phosphorus, iron, sodium, potassium, magnesium and zinc).

In order to facilitate data interpretation, we present calorie[65] and nutrient consumption relative to the dietary reference intakes[66]. The calorie calculations follow Smith et al. (2006) in determining the daily-required calorie consumption per household member taking into account age, sex and breastfeeding. Dietary reference intakes for macronutrient, vitamin and mineral consumption are derived from Meyers et al. (2006), including maximum values to ensure consumption remains under toxicity levels.[67] Macro- and micronutrient consumption requirements for the average household member are adjusted according to the calculation of their necessary calorie consumption (that is based on age, sex and breastfeeding status). For example, if the average household member is recommended to consume 2200 kcal per day, then their recommended protein, carbohydrate and fat consumption are scaled upwards from the standard recommendations for a 2000 kcal diet.[68]

We record total protein as well as animal-sourced protein as proteins found in animal products such as meat, fish, poultry, eggs and dairy products contain all nine essential amino acids necessary for the body's growth, maintenance and repair. These protein sources are called "complete proteins", as opposed to plant-sourced proteins found in nuts, seeds, legumes, grains and vegetables, which tend to be deficient in one or more of the essential amino acids (Meyers et al., 2016). We therefore use the same DRI for total protein and animal-sourced protein to highlight shortcomings in amino acid consumption when animal proteins are insufficiently consumed.

[65] For ease of writing we will continue to include calories when referring to nutrients although they are not technically so. The same will hold for sugar and fiber, subcategories of carbohydrates.

[66] Dietary reference intakes (DRI) include 4 subsets of recommendations. We use the recommended dietary allowance (RDA), determining the average daily dietary nutrient intake level that is sufficient to meet the nutrient requirements of nearly all (97–98 percent) healthy individuals in a particular life stage and gender group, and the tolerable upper intake level, the highest average daily nutrient intake level that likely poses no adverse health risks to almost all individuals in the general population (Meyers et al., 2006).

[67] The dietary reference intake values of nutrients such as saturated fat, cholesterol and sugars are the maximum values for which they do not negatively impact health.

[68] For nutrients that are potentially unhealthy when overconsumed, adjustments are only made for calorie consumption below 2000 kcal and maximum levels are maintained for all daily recommended calorie consumption exceeding 2000 kcal. For vitamins and minerals, we ensure they do not exceed toxicity levels.

5.3 Results

5.3.1. Diary vs recall modules

We start by reporting average percentage deviations from dietary recommendations, calculated over the ca. 500 households given each of the six survey modules. In the results in Table 1 and 2, positive values represent the percentage by which the requirement is exceeded and negative values are the percentage shortfall from the requirements.[69] For example, for the sample using individual diaries, calorie consumption appears to be 20% above the requirements, while animal protein consumption is 51% below requirements. The results for the sample using individual diaries in column (1) serve as a benchmark to compare with the results from the other survey approaches, given that the individual diary is the most resource intensive survey approach that should come closest to the truth. If the household diaries are used instead of the individual diaries, calories appear to be only 7% (for frequent visits) or 12% (for infrequent visits) above requirements while animal protein appears to be 61% (for frequent visits) or 56% (for infrequent visits) below the recommended dietary allowances.

In column (4) of Table 1, we display the mean consumption levels across all three types of diaries. It is evident that the main dietary components below requirements are animal protein, fat, cholesterol, vitamin B9, vitamin E, calcium, sodium and zinc. Thus, a rise in the consumption of animal products and healthy fats would improve the diets of these households.

Table 2 presents similar results to Table 1, but for the samples given recall modules. According to these modules, calories seem almost exactly at the recommended dietary allowance, despite the more accurate individual diaries suggesting that calorie consumption was 20% greater than the requirement. This discrepancy carries through to the apparent individual nutrient consumption. We find similar patterns across nutrients as in Table 1, but with noticeably different magnitudes. For example, consumption of animal protein seems to be 62 - 69% below the requirement compared to 51% below in the benchmark results. It is the 7-day recall that most closely mirrors the personal diary results,

[69] We use the percentage relative to DRIs as this provides a comparable and understandable measure, as opposed to reporting our findings in grams, for example. This measure also provides more information and variation than a simple binary distinction of consuming sufficiently or not. Table A1 portrays the percentage of households consuming under the DRIs per diary module. We find that according to the individual diaries, about 37% of the households in our sample consume under the recommended amount of calories, 86% under the DRI for animal protein and 71% under the DRI for fat. However, from this prevalence measure we have no information about how far under the DRIs these households lie.

although it still overstates the amount by which dietary needs are not being met. The greatest discrepancy from the benchmark results comes from using the 14-day recall module.

In order to empirically test differences in apparent nutrient consumption by module, we use a regression analysis. Our ordinary least squares model has the following structure:

$$N_{ik} = \beta_k M_k + e_{ik} \quad (1)$$

where N_{ik} represents the percentage of nutrient consumed relative to the dietary reference intake, by average household member i assessed using questionnaire k. M_k is a vector of dummy variables for each module type where the personal diaries become our reference category, and e_{ik} is the error term.

Table 3 shows how apparent macronutrient consumption relative to daily recommendations vary by module, where the sample given the personal diary module are the reference group. If diaries are conducted at the household level, with one single diary recorder, they show lower levels of macronutrient consumption. This is apparent with both frequent and infrequent enumerator visits. Thus, it appears that relying on a single recorder rather than on individual recording is the design dimension that seems to affect the data.

The understatement of macronutrient consumption is even more apparent when a 14-day recall (again with a single reporter per household) is used. If a 7-day recall is used, with either type of recall list (58 food and drink groups or 17 major items) there is a consumption overstatement of carbohydrates, sugar, fiber and (for the subset list) calories, with protein and cholesterol understated. These patterns may reflect a household respondent remembering a higher consumption of starchy foods like maize, rice, bread and cakes than is truly the case. Another reason for overstatement may be that because the recall modules were unbounded, with no initial visit to mark the start of the recall period, telescoping errors could cause respondents to report consumption occurring before the recall period as if it happened during the recall period.

Table 4 shows how apparent consumption of vitamins vary by survey module. For the frequently visited household diary and 14-day recall, the discrepancies from the benchmark are often around 20% or larger. These are lower and less prominent for the infrequently visited household diaries. Apparent consumption using 7-day modules are more diverse, with vitamin B2, B3 and B12 understated, but vitamin B6, B9, C and E overstated. If the subset food list is used, all vitamin consumption, bar vitamin B3 and B12, appears to be overstated.

Table 5 presents similar findings for mineral consumption. For the sample given the benchmark diaries, calcium consumption averaged 44% below requirement, as seen from the constant term in Table 5 (and from Table 1). Yet, consumption would seem even lower, by a further factor of up to 14% points (for 14-day recall) if the other survey modules were used. The pattern of understated consumption holds for most minerals, except potassium and magnesium, and is especially apparent if household diaries or the 14-day recall are used. In contrast, the 7-day recall using the full food list provides slight understatements in the consumption of calcium, phosphorus and sodium, but an overstatement in potassium, magnesium and zinc consumption. The 7-day recall using the subset list of foods is more likely to overstate mineral consumption. It must be noted that minerals coming from foods that are difficult to record i.e. sodium from salt, are more likely to be understated across the board.[70]

5.3.2. Heterogeneity analysis

Various household characteristics may affect module performance. For example, a more educated respondent may provide more accurate reports of food consumed over the past period and this may matter more as the period lengthens compared to a daily diary entry (especially as interviewers and survey assistants checked daily). On the other hand, households in urban areas or with more wealth likely consume a greater variety of food, adding to the complexity of the reporting task, especially for recall modules. Lastly, household size and how many young children are present in the household could affect the focus of the respondent and the time spent on diary recording. In other words, the potential accuracy of some of the designs depends more heavily on respondent characteristics than is the case for other designs. Therefore, we run similar regressions to those in section 5.3.1., but now including several selected household characteristics and an interaction term between the household characteristic and module type, as follows:

[70] The results presented in Table 3, 4 and 5 determine the effect that module types have on nutrient consumption on a one-by-one basis. However, in total we assess these effects on 25 outcomes, therefore raising the possibility of multiple hypothesis testing errors. Using the Holm (1979) sequentially-rejective Bonferroni method, we reconsider the significance of individual coefficients when viewed as a family of n hypothesis, ranking the n outcomes in increasing order of their p-values i.e. $p_1 \leq p_2 \leq \cdots \leq p_n$. $p_1 \leq \alpha/n$ to reject the null effect of the outcome with the smallest p-value. If this is the case, the null effect of all following outcomes can also be rejected. Therefore, the smallest p-value in our analysis must be significant at for example the 0.04% level instead of that at the nominal 1% level, or at the 0.2% level instead of at the nominal 5% level. We confirm that this is the case for our results as we have multiple coefficients with a p-value of 0.000. Thus, our findings remain robust to potential family-wise errors.

$$N_{ik} = \beta_k M_k + \beta_x X_{ik} + \delta_k M_k X_{ik} + e_{ik} \quad (2)$$

where X_{ik} is a single household characteristic and δ_k represents the coefficient for the interaction term. This equation is estimated individually, per household characteristic. The household characteristics we use are household size, education of the household head, household wealth, the share of children under 6 and whether the household lives in an urban area.

Table 6 presents a summary of the results of the heterogeneity analysis (full regression tables in online appendix). Panel A of this table shows which modules have positive (non-bold) or negative (bold) interaction effects for the household characteristic indicated in the column when assessing the consumption of the nutrient indicated in the row. Panel B of Table 6 summarizes these results by simply counting per characteristic and per module how many statistically significant (at the 5% level) interaction effects there are. When interpreting panel B it is useful to keep in mind that panel A assesses the modules for 25 nutrients across 5 household characteristics and so is assessed 125 times. From panel B we can see that the characteristics that appear to matter most to the relative performance of survey modules are household size and urban location, with 32 and 36 significant interaction effects. Household wealth, education of the household head and the share of children under 6 have far fewer significant interaction effects (16, 13 and 11, respectively, out of a possible total of 125).

For household size, it appears that respondents in larger households report relatively less when using recall modules (of either 7 or 14 day duration). The effect holds for all minerals, for all vitamins except vitamin B2, B12 and E, and for calories and protein. In other words, the gap between the consumption measured when using benchmark individual diaries and what is measured using recall methods is bigger for larger households. This pattern is consistent with prior evidence of recall surveys increasingly understating food consumption as household size grows, because larger households have more people to report on and so in a given time interval will have more food transactions to recall (Gibson & Kim, 2007). In contrast, almost no nutrient consumption is differentially affected by household size when various types of diaries are used.

Whether the household is in a rural or urban area also seems to matter. Recall modules often seem to mistakenly understate the macro- and micronutrient consumption of urban households compared to what the benchmark shows. Recall likely misses more complex urban consumption patterns that are less reliant on common-pot eating; thus, a recall respondent in an urban area may be less informed about the food consumption of the other household members

than is the case in a rural area. As can be seen from column (3) this is not a pure wealth effect, as wealth has half the number of significant interaction effects.

Finally, the share of children under 6 years of age and the years of formal education of the household head have the lowest count of significant interaction effects and the effects are concentrated overwhelmingly in the recall modules.

Looking at the last column in panel B, which summarizes the total number of significant interaction effects across all 5 modules, we see that the household diaries have much lower counts than the recall modules. All recall modules have many significant interaction effects. Especially the 7-day recall stands out, with 36 significant effects out of a total of 125 possible effects. These patterns confirm that the potential accuracy of some module designs, particularly recall modules, are more subject to variation according to respondent characteristics than is the case for other designs.[71]

5.3.3. Food poverty

Where analysts lack data on food quantities consumed or surveys do not have the required granularity in food items to accurately determine macro- and micronutrient consumption, there may be interest in comparing the value of total food consumption expenditures against a minimum threshold. These comparisons may also be motivated by the insight that interventions to improve nutrition ultimately have to be budgeted for, and so monetary-based calculations can be useful because they are in the same metric (dollars or TZ shillings in this case) that is used when nutritional intervention programs are funded. We conduct such an exercise with two thresholds.

In the first we use linear programming to determine, per region, the minimal cost of a diet that meets all caloric and nutrient requirements per adult equivalent capita (Allen, 2017). We call the diet in question the MC diet and the corresponding cost the MC diet poverty line. We then compute the share of households whose food expenditures lie below the MC diet poverty line. This provides a minimum bound on the calculation of nutrient deprived households: we can be sure that these households are facing nutrient deficiencies, although

[71] Note that the 5% level is chosen to assess the significance for individual outcomes, however, if we were to assess significance in a multiple hypothesis testing context, we would have to determine which module types interact significantly with household characteristics at the 0.2% level. In doing so, we find that most interactions become insignificant, except those for the 7-day recall modules. It remains the case, therefore, that the 7-day recall is more sensitive to household characteristics compared to other survey modules when taking possible family-wise errors into account.

we cannot be sure that those whose value of food consumed is above the threshold are eating healthy diets. For those with a food consumption shortfall, we also calculate the average gap between the value of the household's food consumption and the price of the MC diet in their region.

The second threshold calculates the cost of the typical diet of the 40% poorest to ensure it provides sufficient calories for the household. If the typical diet of the 40% poorest in a region provides, say, 1800 calories, then the cost of this diet is scaled up by 2000/1800 to meet the target recommended calorie intake. We call this the food poverty line (as the scaled basket is one component of cost-of-basic-needs poverty lines). We also calculate the share of households whose food expenditures lie below it and, conditional on that, the average gap.

Both poverty lines are calculated using the highly supervised individual diaries, which we believe contain the most accurate information on prices and expenditures. For the MC diet, prices are median region-level unit prices for each of the 99 food items recorded in the diaries. Ideally, we would have used a price survey for this exercise, but the one conducted as part of this survey experiment was not done with sufficient granularity to confidently calculate the least cost diet.

Table 7 shows the two poverty lines, broken down by region. A number of interesting facts emerge. First, the food poverty line is much higher than the MC diet poverty line in all regions. The diets of the poorest 40% are 2-3 times more expensive than what would be strictly needed to meet all nutrient requirements. Second, there is much more regional variation in the food poverty line than in the MC diet poverty line. Especially Dar es Salaam has a higher poverty line than other regions, which is less evident from Dar es Salaam's MC diet poverty line. Therefore, the higher food poverty line is not just due to higher prices in Dar es Salaam, but also reflects consumer choice for more expensive sources of macro- and micronutrients.

Another interesting example is Pwani, which has the cheapest MC diet at TZS 228 per person per day, yet the food poverty line in Pwani is the highest after Dar es Salaam, at TZS 746 per person per day. Thus, it appears that consumers in Pwani are choosing relatively higher-priced macro- and micronutrients. In this specific case, this could perhaps be due to a local culture of eating foods away from home.

Finding that the food poverty line is much higher than that of the MC diet poverty line, may insinuate that the food consumption of Tanzanian households suffices. However, if we calculate the percentage of households within the 40% poorest income group that consume under the dietary reference intakes, we find that this is not the case. Although spending more than what is

necessary to fulfil all nutritional needs, about 44% of these households consume too little in terms of calories, 88% in terms of animal protein and 80% in terms of fat. Vitamin and mineral deficiencies are also prevalent for more than half of this subsample. These findings echo other data from Tanzania on child stunting levels, at about 42% at the time of this survey experiment, and still remaining high at about 32% in 2018 (World Bank, 2018).

Let us now look at how the different survey methods would assess the prevalence and depth of food poverty compared to these lines. We do so by comparing total household food expenditures, as measured by each of the modules, to the region-specific poverty lines listed in Table 7. Table 9 does this for the set of MC diet poverty lines, with panel A showing the percentage of households whose food expenditures fall below the threshold and panel B the percentage of the shortfall per person per day, i.e. the average proportionate gap for the food-poor.[72]

Table 9 portrays a situation that is consistent with the results for understated nutrient consumption. The 14-day recall overestimates the prevalence of extreme food poverty, suggesting that 11% of people in Tanzania live in households where total food expenditure is below what is needed to buy the MC diet. This is more than twice the rate of extreme food poverty shown with the benchmark individual diary. Likewise, with the 14-day recall, the poverty gap of the food poor is overstated by about one third. In contrast, the infrequent household diary and 7-day recall modules perform most closely to the individual diaries at the national level, although with several discrepancies at the regional level.

Another instructive exercise is to sum the value of all food consumption shortfalls in our sample. A hypothetical perfectly targeted transfer of this size could give all households the freedom to eat a healthy diet without compromising on current non-food expenditures. Of course there is no guarantee that households would spend this amount on nutritious food, nor that the transfer would not spillover into increasing non-food expenditures, but it is a useful benchmark to keep in mind how much households are short when it comes to purchasing a healthy diet. According to the personal diaries, our hypothetical transfer programme would need to provide each MC diet food poor household 60 TZS per person per day to lift it up to the MC diet line. Extrapolating the 4.73% of the total sample under this line to the 57 million people in the whole

[72] Table A2 contains similar results for the food poverty line. The findings are similar to those in Table 9, but with higher rates of households with food expenditures below the threshold and with larger shortfalls.

of Tanzania implies a cost of just under TZS 162m in total per day or about USD 51m a year.[73] However, if we were to budget based on the guidance provided by a 14-day recall survey, the estimated cost would be over $100 million higher, at USD 159m per year, which is a significant bias in the forecast costs. Carrying on with these calculations, the 7-day recall gives a much more reasonable estimate, putting the cost of perfectly targeted transfers at USD 69m.[74]

5.4 Discussion and Conclusions

Using a unique survey experiment, we have been able to assess survey performance in recording macro- and micronutrient consumption, as well as food poverty rates, across 3000 households in Tanzania. Our analyses are motivated by two factors: the growing attention to the nutrition transition means that the focus of many interventions is moving beyond calories; and, some of the most available sources of information are multi-topic household surveys. Yet, even while the confluence of these two factors may see more nutritional analyses based on data from multi-topic household surveys, a threat to the validity of these analyses is that the food consumption modules of these surveys differ in several key dimensions. While these issues have been studied before, especially in the collection of articles introduced by Zezza et al. (2017), there remains much that is unknown, especially when the focus moves beyond calories.

One of the key results to emerge from the current experiment is that the 14-day recall modules led to the largest understatements of both macro- and micronutrient consumption. The 7-day recall module is found to perform closest to the personalized diaries, although particular attention to cereal and other carbohydrate consumption must be considered when using this module design. Household diaries also prove to be less accurate than highly supervised individual diaries, with it being the reliance on a single reporter rather than the frequency of enumerator visits that seems to matter. Comparing survey modules in terms of their performance at the nutrient level as well as at the calorie level has also proven important, with greater sensitivity of apparent protein, cholesterol and fiber consumption than is shown for calorie consumption. Apparent vitamin and mineral consumption also varies substantially with choice of survey module, which has important implications for surveys that aim to take dietary quality measures into account. Previous findings focusing solely on calories may

[73] The average exchange rate during the study period was TZS 1,150 for one USD.

[74] These values are much higher if calculated based on the food poverty line and food poverty shortfall from Table A6, at USD 2.119 billion for personal diaries, USD 3.418 billion for the 14-day recall and USD 2.293 billion for the full food list 7-day recall.

therefore understate the lack of robustness of nutritional indicators to the variation in survey methods.

Furthermore, we found that recall modules are more sensitive to household characteristics than diary modules are. For example, larger household size and urban location are cause for recall modules to further underestimate actual consumption levels. It seems that having more members to recall for, a more diverse availability of foods, and less reliance on common-pot eating in urban areas can make recall modules relatively more difficult for respondents. Education levels of the household head and wealth had slightly less effect on the results.

In our experiment the diary modules generally perform better than the recall modules overall. First, the intensively monitored individual diary is judged as sufficiently close to the truth that we can use it as a benchmark. Second, the other diary modules have results that are less affected by respondent characteristics than is the case for the recall modules, and give results that are fairly close to the benchmark. We caution that this good performance of the diary modules may not translate into other settings. We had great cooperation from respondents, and interviewers were skilled and experienced, and more intensively trained and supervised than typical for developing country surveys. Thus, common diagnostics of problems with diary surveys, such as incomplete diaries or fatigue as the diary-keeping period progresses, are not apparent in this experiment (Beegle et al., 2012). In contrast, in other experiments, and under more usual field conditions with statistics offices, diary surveys often have many partially completed or incomplete records and rates of compliance are likely to vary with household characteristics so the missing information is not missing-at-random (Sharp et al., 2019).

Policy Implications

Accurate measurement of macro- and micronutrient consumption is needed for policymakers to be informed about the scale of nutritional problems and to be equipped with tools that can help to monitor the impact of interventions that aim to overcome these problems. A key finding from our study is that the disparities in apparent nutrient consumption between survey modules are also observed when we compare the value of food consumption with food poverty lines. In particular, all module designs except for the 7-day recall would overestimate the prevalence and depth of food poverty in Tanzania. Consequently, any calculation of possible cash or in-kind transfer programs to eliminate food poverty would likely lead to agencies making excessive budgetary requests if the evidence base was built with surveys such as these. These excessive budgetary

requests could affect the political feasibility of attempting to eliminate hunger with targeted transfers.

Although each survey design comes with potential benefits and shortcomings, the results here could be taken as support for the FAO/WB recommendations for food consumption surveys to use the 7-day recall, rather than longer period recall or diaries (Zezza et al., 2017). In particular, we find that 7-day recalls are relatively good at predicting average nutrient consumption, and also provide good predictions for the prevalence and depth of food poverty. Thus, such surveys could be a reasonable basis for estimating the needed scale of transfer programs designed to alleviate food poverty.

Suggestions for Future Research

Notwithstanding the point above that these results could be taken as support for the FAO/WB recommendation to use 7-day recall surveys for food, there is still much that we do not know. In particular, we caution that even though the nutrient consumption values recorded through the 7-day recall are more likely to be correct on average than other modules, this design is rather sensitive to household characteristics. One reason for this, explored in some detail in Friedman et al. (2017), is that the 7-day recall has offsetting errors that seem to roughly balance: there are incidence errors within several important food groups (that is, entirely forgetting to report any consumption) that are offset by the overstatement of the value of what was consumed conditional on reporting any consumption. One explanation for this pattern is telescoping errors, where consumption that occurred before the recall period is reported as if it was in the recall period; such errors will have a larger impact on a 7-day recall than on a 14-day recall (as they are amortized over fewer days). Hence, a recommendation for any future experiments on this topic is to include treatments that can inform about telescoping, such as the use of an initial visit to bound the recall period.

5.5 References

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5.6 Tables

Table 1 | Differences in the percentage of nutrient consumption per diary module

	(1)	(2)	(3)	(4)
Percentage consumption relative to DRI	Individual diary, frequent visits, 14 days	Household diary, frequent visits, 14 days	Household diary, infrequent visits, 14 days	Total
Calories	20.28	6.687	11.89	12.96
Macronutrients				
Protein	44.74	25.43	34.83	35.01
Animal protein	-50.55	-61.14	-56.19	-55.96
Fat	-11.03	-24.70	-20.72	-18.81
Saturated fat	63.69	34.42	44.35	47.50
Cholesterol	-74.57	-82.46	-78.18	-78.41
Carbohydrates	50.72	37.39	44.62	44.25
Sugars	33.06	10.13	19.51	20.91
Fiber	66.28	49.33	56.33	57.32
Vitamins				
Vitamin A	34.45	13.13	23.85	23.81
Vitamin B1	25.18	13.56	20.14	19.63
Vitamin B2	164.4	135.8	165.3	155.2
Vitamin B3	40.13	23.54	29.59	31.09
Vitamin B6	75.39	52.99	61.48	63.29
Vitamin B9	2.269	-9.898	-1.867	-3.163
Vitamin B12	72.09	32.03	38.96	47.72
Vitamin C	38.44	17.65	27.71	27.94
Vitamin E	-8.996	1.650	-4.588	-3.981
Minerals				
Calcium	-44.48	-51.74	-47.77	-47.99
Phosphorus	103.8	80.89	91.68	92.12
Iron	34.82	20.58	27.50	27.64
Sodium	-52.83	-58.71	-57.95	-56.49
Potassium	19.36	6.618	12.35	12.78
Magnesium	48.00	35.59	44.20	42.60
Zinc	-1.267	-12.86	-5.389	-6.502

Table 2 | Differences in the percentage of nutrient consumption per recall module, original food groups

Percentage consumption relative to DRI	14 day recall	7 day recall	7 day recall (subset of food groups)	Total
Calories	0.587	0.409	0.415	0.470
Macronutrients				
Protein	6.165	25.26	23.73	18.38
Animal protein	-69.23	-62.86	-67.59	-66.56
Fat	-37.55	-24.92	-29.14	-30.54
Saturated fat	14.47	36.80	51.50	34.26
Cholesterol	-80.70	-77.65	-85.88	-81.41
Carbohydrates	39.70	65.11	84.78	63.20
Sugars	22.98	53.87	34.86	37.24
Fiber	56.94	87.32	91.51	78.59
Vitamins				
Vitamin A	14.36	23.92	81.98	40.08
Vitamin B1	11.85	30.01	47.21	29.69
Vitamin B2	90.61	124.9	191.0	135.5
Vitamin B3	12.05	32.06	26.81	23.64
Vitamin B6	67.10	99.90	113.6	93.54
Vitamin B9	15.65	37.57	44.64	32.62
Vitamin B12	-3.289	4.884	38.79	13.46
Vitamin C	45.13	71.73	89.36	68.74
Vitamin E	14.89	3.265	7.186	8.448
Minerals				
Calcium	-59.08	-50.60	-45.13	-51.60
Phosphorus	63.00	89.98	106.1	86.36
Iron	17.67	37.00	50.07	34.91
Sodium	-67.40	-60.90	-76.51	-68.27
Potassium	29.36	58.62	67.04	51.67
Magnesium	64.48	95.11	104.2	87.93
Zinc	-8.692	7.193	7.400	1.967

Table 3 | Effect of module type on apparent macronutrient consumption as a percentage of the dietary reference intakes

VARIABLES	(1) Calories	(2) Protein	(3) Animal protein	(4) Fat	(5) Saturated fat	(6) Cholesterol	(7) Carbohy-drates	(8) Sugars	(9) Fiber
Diary: HH, frequent	-13.60***	-19.31***	-10.59***	-13.67	-29.27	-7.890***	-13.33***	-22.93***	-16.95***
	(5.125)	(4.462)	(2.604)	(14.06)	(40.51)	(1.652)	(4.675)	(6.427)	(5.621)
Diary: HH, infrequent	-8.389	-9.912**	-5.633**	-9.689	-19.35	-3.610**	-6.102	-13.55**	-9.958*
	(5.127)	(4.464)	(2.605)	(14.06)	(40.53)	(1.653)	(4.677)	(6.430)	(5.624)
Recall: Long, 14 day	-16.93***	-38.58***	-18.68***	-26.52*	-49.22	-6.129***	-11.02**	-10.07	-9.342*
	(5.120)	(4.457)	(2.601)	(14.04)	(40.47)	(1.650)	(4.670)	(6.420)	(5.615)
Recall: Long, 7 day	1.835	-19.48***	-12.31***	-13.89	-26.89	-3.072*	14.39***	20.81***	21.04***
	(5.120)	(4.457)	(2.601)	(14.04)	(40.47)	(1.650)	(4.670)	(6.420)	(5.615)
Recall: Subset, 7 day	11.70**	-21.02***	-17.04***	-18.11	-12.19	-11.31***	34.06***	1.801	25.22***
	(5.120)	(4.457)	(2.601)	(14.04)	(40.47)	(1.650)	(4.670)	(6.420)	(5.615)
Constant	20.28***	44.74***	-50.55***	-11.03	63.69**	-74.57***	50.72***	33.06***	66.28***
	(3.622)	(3.153)	(1.840)	(9.934)	(28.63)	(1.167)	(3.304)	(4.542)	(3.973)
Observations	3,018	3,018	3,018	3,018	3,018	3,018	3,018	3,018	3,018
R-squared	0.014	0.027	0.024	0.001	0.001	0.019	0.048	0.018	0.031

Note: Each column presents estimates of equation (1), where the left hand side variable is the deviation from the dietary reference intake of the nutrient indicated in the column heading. Standard errors are in parentheses under the coefficient. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4 | Effect of module type on apparent vitamin consumption as a percentage of the dietary reference intakes

VARIABLES	(1) Vitamin A	(2) Vitamin B1	(3) Vitamin B2	(4) Vitamin B3	(5) Vitamin B6	(6) Vitamin B9	(7) Vitamin B12	(8) Vitamin C	(9) Vitamin E
Diary: HH, frequent	-21.32*	-11.63***	-28.58**	-16.59***	-22.40***	-12.17**	-40.06***	-20.79**	10.65
	(11.24)	(3.940)	(12.04)	(4.416)	(6.581)	(4.922)	(14.14)	(8.490)	(6.984)
Diary: HH, infrequent	-10.60	-5.041	0.922	-10.54**	-13.90**	-4.136	-33.13**	-10.73	4.408
	(11.25)	(3.942)	(12.05)	(4.418)	(6.585)	(4.925)	(14.15)	(8.494)	(6.988)
Recall: Long, 14 day	-20.09*	-13.33***	-73.80***	-28.07***	-8.287	13.39***	-75.38***	6.689	23.89***
	(11.23)	(3.937)	(12.03)	(4.411)	(6.575)	(4.918)	(14.13)	(8.482)	(6.977)
Recall: Long, 7 day	-10.53	4.827	-39.54***	-8.062*	24.52***	35.30***	-67.21***	33.29***	12.26*
	(11.23)	(3.937)	(12.03)	(4.411)	(6.575)	(4.918)	(14.13)	(8.482)	(6.977)
Recall: Subset, 7 day	47.53***	22.03***	26.57**	-13.32***	38.25***	42.37***	-33.30**	50.92***	16.18**
	(11.23)	(3.937)	(12.03)	(4.411)	(6.575)	(4.918)	(14.13)	(8.482)	(6.977)
Constant	34.45***	25.18***	164.4***	40.13***	75.39***	2.269	72.09***	38.44***	-8.996*
	(7.944)	(2.785)	(8.513)	(3.121)	(4.651)	(3.479)	(9.995)	(6.000)	(4.936)
Observations	3,018	3,018	3,018	3,018	3,018	3,018	3,018	3,018	3,018
R-squared	0.017	0.035	0.028	0.015	0.041	0.063	0.012	0.033	0.005

Note: Each column presents estimates of equation (1), where the left hand side variable is the deviation from the dietary reference intake of the nutrient indicated in the column heading. Standard errors are in parentheses under the coefficient. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 5 | Effect of module type on apparent mineral consumption as a percentage of the dietary reference intakes

VARIABLES	(1) Calcium	(2) Phosphorus	(3) Iron	(4) Sodium	(5) Potassium	(6) Magnesium	(7) Zinc
Diary: HH, frequent	-7.259***	-22.87***	-14.24***	-5.874**	-12.74**	-12.41**	-11.59***
	(2.317)	(6.044)	(4.269)	(2.389)	(6.032)	(5.379)	(3.258)
Diary: HH, infrequent	-3.294	-12.08**	-7.322*	-5.118**	-7.007	-3.808	-4.122
	(2.318)	(6.047)	(4.271)	(2.390)	(6.035)	(5.382)	(3.260)
Recall: Long, 14 day	-14.60***	-40.76***	-17.15***	-14.56***	10.00*	16.48***	-7.424**
	(2.315)	(6.038)	(4.265)	(2.387)	(6.026)	(5.374)	(3.255)
Recall: Long, 7 day	-6.125***	-13.78**	2.183	-8.067***	39.26***	47.11***	8.460***
	(2.315)	(6.038)	(4.265)	(2.387)	(6.026)	(5.374)	(3.255)
Recall: Subset, 7 day	-0.654	2.342	15.24***	-23.68***	47.68***	56.20***	8.667***
	(2.315)	(6.038)	(4.265)	(2.387)	(6.026)	(5.374)	(3.255)
Constant	-44.48***	103.8***	34.82***	-52.83***	19.36***	48.00***	-1.267
	(1.638)	(4.272)	(3.017)	(1.688)	(4.263)	(3.802)	(2.303)
Observations	3,018	3,018	3,018	3,018	3,018	3,018	3,018
R-squared	0.016	0.022	0.024	0.039	0.055	0.086	0.021

Note: Each column presents estimates of equation (1), where the left hand side variable is the deviation from the dietary reference intake of the nutrient indicated in the column heading. Standard errors are in parentheses under the coefficient. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 6 | Significant interactions between module type and selected household characteristics

Panel A – Significant effects

	Household characteristics				
	(1)	(2)	(3)	(4)	(5)
Percentage consumption relative to DRI	Household size	Education household head	Wealth	Share children under 6	Urban household
Calories	**4**	-	**5**	-	**3, 4**
Protein	**4**	**1**	3, 4	**4**	**-**
Animal protein	-	**-**	**1,** 3, 4, 5	**4**	**1,** 3, 4, 5
Fat	5	-	**5**	-	-
Saturated fat	5	-	**5**	-	-
Cholesterol	-	**1, 5**	**1, 2**	**-**	**1, 2**
Carbohydrates	**3, 4, 5**	**4, 5**	**5**	**-**	**3, 4, 5**
Sugars	1, **4, 5**	-	5	-	-
Fiber	**3, 4, 5**	**4, 5**	**5**	-	**3, 5**
Vitamin A	**5**	-	-	-	**5**
Vitamin B1	**3, 4, 5**	**4, 5**	**5**	**-**	**3, 4, 5**
Vitamin B2	**-**	-	**2**	-	-
Vitamin B3	**4**	-	-	-	**3, 5**
Vitamin B6	**3, 4, 5**	-	-	**4, 5**	**3, 4, 5**
Vitamin B9	**3, 4, 5**	-	-	**4, 5**	**5**
Vitamin B12	-	-	**1**	-	**1, 2**
Vitamin C	**4**	-	**5**	**4, 5**	**5**
Vitamin E	4	-	-	-	5
Calcium	**3, 4, 5**	-	3, 4, 5	**3, 4, 5**	3, 4
Phosphorus	**3, 4, 5**	**-**	-	**4**	**5**
Iron	**3, 4, 5**	-	-	**-**	**3, 4, 5**
Sodium	**4**	3, 4	3, 4	**3, 4**	3, 4
Potassium	**3, 4, 5**	-	**5**	**5**	**3, 4, 5**
Magnesium	**4, 5**	**3, 4, 5**	**3, 4, 5**	-	**3, 4, 5**
Zinc	**4**	**3**	-	**4**	-

Panel B – Count of significant effects in panel A

	(1)	(2)	(3)	(4)	(5)	(6)
	House-hold size	Education house-hold head	Wealth	Share children under 6	Urban house-hold	TOTAL
1. Diary: HH, frequent	1	1	2	0	3	**7**
2. Diary: HH, in-frequent	0	0	1	0	2	**3**
3. Recall: Long, 14 day	9	2	5	2	12	**30**
4. Recall: Long, 7 day	11	5	5	5	10	**36**
5. Recall: Subset, 7 day	11	5	3	4	9	**32**
TOTAL	**32**	**13**	**16**	**11**	**36**	**108**

Note: Panel A shows the results of estimating equation (2) separately for each combination of nutrients indicated in the row and the household characteristic indicated in the column. The cells indicate for which module the interaction effects are significant at the 5% level, with a bold number representing a negative coefficient and a non-bold number a positive one. The modules are represented with the following numbers 1 (Diary HH, frequent), 2 (Diary HH, infrequent), 3 (Recall 14 days), 4 (Recall 7 days), 5 (Recall 7 days subset). A dash (-) means there are no positive effect for any module for that combination of nutrient and household characteristic. Panel B then counts the number of significant effects in panel A (positive or negative) per module and per household characteristic.

Table 7 | Minimum cost diet and cost of basic needs food poverty lines per region

	Minimum cost diet food poverty line (TZS)	Cost of basic needs food poverty line (TZS)
Dodoma	320.17	710.40
Pwani	227.84	746.08
Dar es Salaam	411.76	1444.25
Shinyanga	310.42	617.94
Kagera	257.75	695.46

Table 8 | Percentage of households consuming under the dietary reference intakes, from the poorest 40% households

Percentage of households consuming under the DRI	Individual diary, frequent visits, 14 days
Calories	43.70
Macronutrients	
Protein	34.00
Animal protein	87.30
Fat	79.70
Saturated fat	65.00
Cholesterol	98.50
Carbohydrates	17.30
Sugars	50.30
Fiber	15.20
Vitamins	
Vitamin A	62.40
Vitamin B1	37.60
Vitamin B2	17.80
Vitamin B3	35.50
Vitamin B6	7.61
Vitamin B9	57.90
Vitamin B12	71.10
Vitamin C	29.40
Vitamin E	55.30
Minerals	
Calcium	84.80
Phosphorus	16.80
Iron	40.10
Sodium	94.40
Potassium	23.90
Magnesium	20.30
Zinc	64.50

Table 9 | Extreme food poverty

Panel A: Households spending below minimum cost diet threshold (%)

	Dodoma	Pwani	Dar es Salaam	Shinyanga	Kagera	Total
Diary: Personal	5.65	9.64	0.00	6.77	1.25	4.73
Diary: HH, frequent	7.37	1.61	1.69	14.47	4.55	7.61
Diary: HH, infrequent	6.85	2.31	3.83	11.28	2.09	6.19
Recall: Long, 14 day	4.79	3.10	0.00	22.70	6.90	11.35
Recall: Long, 7 day	1.96	3.35	0.00	16.39	4.89	7.77
Recall: Subset, 7 day	8.65	0.00	0.93	22.09	2.26	9.54

Panel B: Average poverty gap of the food-poor (%)

	Dodoma	Pwani	Dar es Salaam	Shinyanga	Kagera	Total
Diary: Personal	17.43	14.20	0.00	24.70	5.38	19.63
Diary: HH, frequent	29.17	41.59	17.65	19.69	17.06	20.91
Diary: HH, infrequent	24.41	4.51	5.74	17.32	25.67	17.50
Recall: Long, 14 day	17.76	11.60	0.00	27.29	22.23	25.39
Recall: Long, 7 day	2.76	2.30	0.00	19.11	9.96	16.04
Recall: Subset, 7 day	8.20	0.00	14.25	13.86	31.36	14.32

5.7 Appendix

Table A1 | Differences in the percentage of households consuming under the DRI, per diary module

	(1)	(2)	(3)
Percentage of households consuming under the DRI	Individual diary, frequent visits, 14 days	Household diary, frequent visits, 14 days	Household diary, infrequent visits, 14 days
Calories	36.80	46.00	43.50
Macronutrients			
Protein	30.20	40.80	37.70
Animal protein	86.30	94.00	91.20
Fat	71.00	75.90	75.40
Saturated fat	47.50	51.60	50.30
Cholesterol	97.60	99.20	97.80
Carbohydrates	14.90	22.90	18.40
Sugars	40.80	52.00	48.90
Fiber	17.10	26.10	24.20
Vitamins			
Vitamin A	53.10	59.60	56.90
Vitamin B1	38.60	45.80	40.30
Vitamin B2	15.50	19.10	19.20
Vitamin B3	32.20	43.00	38.30
Vitamin B6	10.10	15.70	14.40
Vitamin B9	59.80	71.50	63.30
Vitamin B12	59.00	66.30	63.70
Vitamin C	37.60	48.00	44.50
Vitamin E	55.70	63.90	59.10
Minerals			
Calcium	88.70	92.80	88.80
Phosphorus	13.50	19.10	15.80
Iron	36.80	46.00	42.10
Sodium	92.80	94.60	95.00
Potassium	31.00	42.40	40.50
Magnesium	18.90	24.30	20.00
Zinc	59.60	66.30	59.90

Table A2 | Cost of basic needs food poverty

Panel A: Percentage of households spending below threshold

	Dodoma	Pwani	Dar es Salaam	Shinyanga	Kagera	Total
Diary: Personal	23.22	48.69	53.30	43.06	47.78	43.75
Diary: HH, frequent	43.95	70.30	76.81	60.04	53.74	60.05
Diary: HH, infrequent	31.11	68.21	65.51	51.13	57.52	54.43
Recall: Long, 14 day	39.80	63.02	45.56	76.58	56.47	61.64
Recall: Long, 7 day	25.09	53.08	30.21	57.18	50.53	47.38
Recall: Subset, 7 day	36.41	48.80	44.84	68.74	46.69	53.25

Panel B: Average poverty gap of the food-poor

	Dodoma	Pwani	Dar es Salaam	Shinyanga	Kagera	Total
Diary: Personal	30.80	42.15	31.52	31.38	27.56	31.76
Diary: HH, frequent	35.01	33.56	38.29	34.07	32.73	34.43
Diary: HH, infrequent	28.46	37.26	42.70	30.36	29.37	32.92
Recall: Long, 14 day	23.22	31.86	32.48	38.28	40.68	36.37
Recall: Long, 7 day	25.44	30.02	28.30	35.18	29.99	31.74
Recall: Subset, 7 day	36.04	30.70	27.25	37.56	28.81	33.47