Essays in Development Economics and Global Health

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Submitted by

Markus Heemann

Born on 26.05.1992 in Stuttgart, Germany

First academic advisor:	Prof. Dr. Sebastian Vollmer
Second academic advisor:	Prof. Dr. Andreas Fuchs
Third academic advisor:	Prof. S. V. Subramanian, Ph.D.

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Chapter I

Introduction

I.1 Background and Motivation

Ever since the revision of the Millennium Goals in 2015, which became known as the Sustainable Development Goals (SDGs), the research fields of development studies and development economics have been provided with a clear research framework with broad sets of research questions. This framework comprises many aspects that all aim to contribute to a more equitable society and ensure minimum standards along different dimensions for every person across the globe. The first and probably most prominent Sustainable Development Goal #1 *No poverty* is followed by #2 *Zero Hunger* and #3 *Good Health and Well-Being*. Even though the SDGs are not ordered according to their relevance, having these three as the first of 18 SDGs does show how much emphasis is being put on them and how much they are considered key policy and research outcomes. This dissertation will mainly focus on these three SDGs, placing particular emphasis on the intersection of SDGs *#2 Zero Hunger* and *#3 Good Health and Wellbeing*, by focusing on under- and malnutrition of young children. However, this dissertation will also address SDG *#1 No poverty*, particularly potential trade-offs between SDG *#1 No poverty* versus SDG *#3 Good Health and Wellbeing*.

Nutrition plays a vital role in people's lives. Under- as well as malnutrition go way beyond the imminent biological need of relieving oneself of hunger. Nutrition plays a crucial part from early age in physical health, resilience, and cognitive development, and as a result also for the quality and subsequent opportunities in life and economic prosperity (Perkins et al. 2017; Patel & Deveraj 2018). Therefore, undernutrition is a key outcome of global academic research and policymakers (Martins et al. 2011; Black et al. 2008). While many children across the globe, particularly in low- and middle-income countries (LMICs), suffer from insufficient calorie intake, research has shown that addressing calorie intake alone does not address all food-related inequalities and dietary needs of children (UNICEF 2022, WHO 2003). Next to consuming sufficient calories, a diverse diet containing a range of different micronutrients is just as important as it has been shown that micronutrients, particularly during the first years of a child's life, have significant consequences for cognitive as well as organ development (Sudfeld et al. 2015; Horten & Steckel 2013). At the same time, overnutrition in forms of overweight and obesity which is linked to multiple co-morbidities, is also of growing concern in LMICs (NCD-RisC Africa Working Group 2017; Ng et al. 2014).

Among the most vulnerable groups across the globe are young children, that by nature, are very limited in their ability to self-help **(**Landrigan 2004**)**. A special focus on children is also justified by the fact that successfully addressing children's needs can have particularly high impacts on society given the large remaining life span and the fact that children form the subsequent generation will be responsible for addressing future challenges of societies (Etzel 2020; Clark et al. 2020). In accordance with the SDGs, the Global Strategy for Women's, Children's and Adolescents' Health was defined to provide "a roadmap for ending preventable deaths of women, children, and adolescents by 2030 and helping them achieve their potential for and rights to health and well-being in all settings" (UNICEF 2019). As part of that strategy, the reproductive, maternal, newborn, child, and adolescent health and nutrition (RMNCAH-N) agenda was laid out to serve as a research framework for academics and policymakers contributing to achieving the SDGs. This RMNCAH-N framework will also be one of the research frameworks guiding this dissertation.

Nutrition, both for adults and children, is linked to households' financial resources, which are often directly related to the employment situation of its household members (Debela, Gehrke and Qaim 2021; Ziol-Guest, Dunifon and Kalil 2013). As a result, labor markets don't just play an important role in SDG *#1 Zero Poverty*, but also for several other SDGs, such as *#2 Zero Hunger*, for instance. Particularly in extreme situations, such as the recent global COVID-19 pandemic, where a lot of stress was put on labor markets (ILO 2021), policymakers need a good understanding of the multiple consequences and potential economic impacts their policies may have. Good examples are the broad mobility restrictions and curfews implemented by many countries following the outbreak of the COVID-19 pandemic.

Since the definition of the Millennium Goals, many indicators have already seen large improvements, but there is still a long way to go (Sachs et al. 2019). For example, the under-5 mortality rate fell by 49% between 2000 and 2017, and extreme poverty declined considerably from >25% in 2000 to ~9% in 2018. These improvements can be attributed to increased attention, more resources in combination with more precise data required to craft effective interventions, as well as the fact that overall, the world has become a more prosperous place. Average yearly economic growth in LMICs since 2000 has stood at roughly four percent and as such has outperformed growth rates seen in high-income countries (World Bank 2022). However, there is still a long way to go. Wars, health crises, international conflicts, and new dynamics such as the possibility of de-globalization, may make it increasingly challenging to achieve the SDG agenda (Sachs et al. 2022). Former answers that used to work may not work anymore. Therefore, continued research will play an important part in ensuring that the Sustainable Development Goals will be met.

This work aims to contribute to the field of literature by addressing questions around how to better capture under- and particularly malnutrition, the current status quo of child under-and malnutrition across large samples of LMICs, how deep child food poverty runs, as well as to what degree it is associated with economic growth. At the same time, it looks at the relationship of mobility with labor market outcomes in the situation of a pandemic that has also affected nutrition across the globe (Headey et al. 2020).

To conduct research of this kind, researchers can build on a large pool of data that is being made available by multiple different sources such as NGOs, research institutes, and governments. Increased data availability has been an important factor contributing to the progress that was made over the past decades (Fabic, Choi and Bird 2012). Increased data availability, quality as well as granularity has significantly augmented researcher's ability to investigate both the status quo for numerous key indicators as well as determine causal mechanisms of various kinds driving the observed status quo. Having global access to high-quality (and standardized) secondary data is an important contribution to international academic research. At the same time, it is important for researchers to generate primary data, given that this is often much more targeted (local, over a specific period of time, etc.) than publicly available secondary data sets. Both sources of data are of importance, which is why this dissertation works with both publicly available sets of secondary data (mostly relying on demographic and health survey data) but also primary data that was collected by the World Bank in Kenya over the course of the COVID-19 pandemic in multiple high-frequency survey waves.

Using this data, research needs to be done on different levels. Global health, food, or wealth inequalities are driven by between-country inequalities as well within-country inequalities (Ravalon 2014). Therefore, to determine needs, monitor progress being made and craft targeted interventions within the Sustainable Goals research framework, it is imperative to conduct research both on a pooled level for multiple countries as well as on the local level. The benefit of conducting research for pooled samples of many countries is that it can both identify global needs and highlight sub-samples that either lack behind and thus are in need of special attention and support or sub-samples that show promising results and thus serve as possible best-practice case studies. Country-specific or even more local research at the same time is important for precise target group identification and the evaluation of locally decided and implemented policies and measures.

I.2 Chapter Overview

The chapters in this dissertation provide insights into different aspects of the SDG research agenda. The chapters also both incorporate publicly available secondary data sources as well as newly collected survey data. Depending on the chapter, analyses were done either for a pooled sample or a single country. Chapters II-V address questions around SDGs *#2 Zero Hunger* and *#3 Good Health and Well-Being,* by incorporating secondary data from between 56-61 different low- and middle-income countries in pooled analyses. Chapter VI addresses the interface of SDGs *#1 No poverty* and *#3 Good Health and Well-Being* by looking at the Kenyan labor market impacts from COVID-19 mobility restrictions. While Kenya has been subject to extensive development research before, it is important to highlight that there are certain restrictions regarding representability of Chapter VI for other low-and middle-income countries, given that Kenya varies considerably in terms of social structure, culture, and political environment from other African countries, let alone other LMICs from Asia or South America.

Chapter II: Assessment of nutritional needs among children: An empirical analysis of diet and anthropometric based measures

The first chapter investigates the commonality of showing signs of anthropometric failure together with the prevalence of not having sufficient dietary diversity (and as such insufficient micronutrient intake) in young children. Children's anthropometric features were commonly used in the past to determine both magnitude of undernutrition as well as defining target groups (Vollmer et al. 2017; Corsi et al. 2011). Therefore, this study's goal was to determine whether physical signs also correlate with micronutrient deficiency, which in itself can lead to significant health and development risks in a child, particularly at a young age (Perkins et al. 2017; Patel & Deveraj 2018; Sudfeld et al. 2015; Krebs 2011; WHO 2003). For this analysis, we pooled demographic and health surveys (DHS) from 55 LMICs that were conducted between 2009-2019.

We found that while there is a certain overlap of children showing signs of anthropometric failure and dietary failure together, overall discordance, measured by children that either showed signs of anthropometric failure only or had dietary failure only, was high (51.2%). Our results imply that anthropometric failure and dietary failure do not go hand-in-hand for young children aged 6-23mth age. Adding children without sufficient dietary diversity to those that only show physical signs of undernutrition more than doubles the number of children in LMICs that suffer from under- and malnutrition. For the sample under investigation, this implied an additional 45.3 million children with unmet dietary needs.

The main contribution of this essay is to show that only looking at physical signs does not capture global under-and malnutrition for young children very well and that achieving minimum dietary diversity should be considered as a key nutrition outcome next to anthropometric failure by researchers. This work provides a justification for further research into minimum dietary diversity and underlying food group and item consumption patterns.

Chapter III: Food group consumption patterns among children meeting and not meeting WHO's recommended dietary diversity

Building on findings from Chapter II, Chapter III investigates in more detail food group and item consumption patterns for a sample of 59 LMICs. Having established that children not meeting WHO's requirement of minimum dietary diversity deserve special focus and given the scarcity of literature looking at food consumption differences between children meeting MDD vs. not meeting MDD (Beckermann-Hsu et al. 2020), this chapter analyses how the diet of children meeting MDD vs. not meeting MDD differed and what socio-economic factors may have played a role in the observed consumption patterns. As in Chapter II, DHS surveys were used from 59 countries.

We found that 73.8% of children did not meet WHO's recommended Minimum Dietary Diversity. Next to confirming the findings of Chapter II that many children in LMICs need a more diverse diet, we showed that inter-food group variation of food item-specific consumption levels varied for different food groups. Our results suggest that to better understand patterns behind minimum dietary diversity and how to increase the share of children fulfilling this requirement, policymakers and researchers need to look at food item level to properly identify needs and opportunities. We establish that particularly protein rich foods, as well as vitamin-dense food groups, deserve a special focus across LMICs. Regression results showed that for different food items, mechanisms like availability, education/awareness, and household resources are of importance.

The contribution of this chapter is the presentation of pooled food consumption data on food item level in LMICs. Furthermore, using data from 59 countries and finding multiple potential drivers of food consumption levels, a framework for policymakers is developed on how to approach the goal of increasing children meeting MDD subject to locally representative data being available.

Chapter IV: The magnitude and depth of child food poverty in low- and middle-income countries: Insights from 200,346 Children in 61 countries.

While Chapters II and III first established minimum dietary diversity's relevance for researchers and policymakers and looked at food consumption patterns behind the binary indicator of meeting MDD, Chapter IV investigates the degree of inequality of micronutrient intake for young infants in low- and middle-income countries. Following UNICEF's concept of child food poverty, we apply Vollmer et al.'s adaptation of commonly used income poverty measure to child food poverty (UNICEF 2022; Vollmer 2023; Foster, Greere and Thorbecke 1984). By doing so, we extend the analysis of shares of children not meeting MDD to how far these children are lacking behind, i.e., how large the gap is to all children consuming at least five food groups.

We found that, firstly, food poverty share stood at 73.7% and the food poverty gap at 35.2%. The distribution of children below the food poverty line was skewed towards the poverty line. This is also reflected by shares of children consuming just one or two food groups less than the recommended five food groups ranging from 40% in Africa and Asia to 32% in South America. We also found that particularly the vitamin-dense food groups showed largest increases (>40%) around the food poverty threshold (for children consuming between three and five food groups). For "Vitamin-A rich fruits/vegetables" overall availability in a country as well as awareness of the importance from early age proved relevant for consumption levels, while for "Other fruits/vegetables" household resources and maternal education also appeared to influence consumption around the food poverty threshold.

The contribution of this chapter is to look beyond minimum dietary diversity as a binary indicator and to analyze the gap that children are lacking behind for a global sample of LMICs. By showing that average missing food groups are consistently around 2, our findings give hope that by implementing targeted food interventions addressing the consumption of up to two food groups, many children may be relieved from child food poverty.

Chapter V: Economic Growth as a Sufficient Condition for Reducing Early Childhood Malnutrition? An Empirical Analysis of the revised UNICEF Conceptual Framework

Previous research has shown that physical signs of undernutrition, i.e., stunting, wasting and/or underweight have shown little improvement as LMICs grew economically over the past decades (Vollmer et al. 2014). The fifth chapter combines these findings with lessons from Chapter II, i.e., that dietary diversity should be considered a key research outcome, as well as research showing overweight/obesity are of growing concern for developing countries (WHO 2014). Overall, it extends the analyses by Vollmer et al. of the association of economic growth with undernutrition outcomes a) by re-conducting the analysis for an even larger sample and b) by showing to which degree economic growth is associated not just with improvements in undernutrition indicators but also additional malnutrition indicators (i.e., insufficient dietary diversity as well as overnutrition indicators). Furthermore, building on the UNICEF conceptual framework of child malnutrition which introduces different hierarchical levels for factors influencing child malnutrition outcomes (Black et al. 2021; UNICEF 1990), this chapter analyses how the association of economic growth with proximal and distal determinants of nutrition outcomes may explain the overall low association of these outcomes with economic growth. This chapter includes data from 58 countries.

At first, the paper confirms previous research findings showing little statistical association of economic growth with children's physical signs of undernutrition. For malnutrition and overnutrition however, we found higher statistical significance and coefficients. Looking at both the association of proximal and distal factors of undernutrition with our outcomes and their individual relationship with economic growth, we concluded that the association of economic growth with proximal and distal factors of undernutrition helps to explain the overall observed association of economic growth with our under- and malnutrition outcomes.

This chapter is novel in that it confirms previous research with the most recent available data, extends the analyses by also incorporating malnutrition outcomes (including overnutrition) and provides insights into the potential channels explaining the magnitude and variation of the association of economic growth with countries' improvement of under- and malnutrition outcomes.

Chapter VI: The Impact of Mobility Restrictions on Labor Markets: Evidence from Nationally Representative Phone Surveys during the COVID-19 Pandemic in Kenya

While this chapter is still related to health as it addresses dynamics over the course of the COVID-19 pandemic, it leaves the topic of nutrition and food security and instead focuses on the labor market effects of the containment measures in Kenya. It takes advantage of high-frequency mobile phone surveys to estimate the causal effects of mobility on labor market outcomes during the COVID-19 pandemic. The relationship between mobility levels and labor market outcomes commonly suffers from reverse causality (Espitia et al. 2021). Leveraging the pandemic and its mobility restriction measures as a natural experiment, this chapter estimates the labor market effects that were caused by changing mobility levels driven by the Kenyan Government's response to the COVID-19 pandemic. Outcomes of interest are employment status as well as hours worked, and income generated. The high-frequency mobile phone surveys that were conducted by the World Bank during the course of the pandemic in Kenya are combined with other data sources to conduct causal inference.

Overall, we found evidence of causal effects of recovering mobility levels on labor market outcomes. The most relevant effects were for extensive margins of employment, i.e., recovering mobility leading to people re-entering the labor force and (un-)employment. Effect sizes and significance for hours worked depended on the type of employment as well as urban/rural residency, while income did not seem to be affected by changing mobility. Our results also showed that for urban and rural households, different factors seemed to be relevant when determining whether to adhere to mobility-reducing guidelines or not.

This paper is one of the first to use causal inference to determine the effect of changing mobility levels on labor market outcomes, particularly in a developing country. As such, the research question as well as the data used are innovative and provide important insights for policymakers on how much influence mobility has on labor market outcomes. This, in turn has important implications for future health-wealth trade-off considerations in situations where mobility needs to be reduced to save lives. Furthermore, this study is one of the first to provide insights into factors associated with self-reported mobility-reducing behavior for a representative sample in a low-and middle-income country setting over the course of the pandemic.

I.3 Conclusion

This dissertation aims to contribute to the Sustainable Development Goal agenda by presenting research that focuses on the first three SDGs *#1 No Poverty*, *#2 Zero Hunger* and *#3 Good Health and Well-being*. More specifically, the five essays forming the main body of this dissertation focus on two distinct aspects, under-and malnutrition of young children as well as labor market effects over the course of the COVID-19 pandemic. By doing so, the dissertation provides answers to questions such as how to properly measure under- and malnutrition, the status quo of magnitude and depth of under- and malnutrition in LMICs, factors that may contribute to the status quo, but also which mechanisms drive labor market outcomes over the course of a health crisis. By leveraging multiple types of representative surveys and conducting research both on a pooled as well as a single country level, this dissertation is able to draw conclusions both for the general public as well as local contexts.

Chapter II

Assessment of nutritional needs among children: An empirical analysis of diet and anthropometric based measures in 55 low- and middle-income countries

With: Rockli Kim, Sebastian Vollmer and S.V. Subramanian

Abstract

Evidence on the suitability of anthropometric failure (i.e., stunting, underweight, and wasting) as standalone measure of child undernutrition can inform global and national nutrition and health agendas. This paper provides a comprehensive estimate of the prevalence of child undernutrition by looking at both dietary and anthropometric measures simultaneously across 55 low- and middle-income countries. Two factors were considered to allocate children into the respective categories. Dietary failure was based on the World Health Organization (WHO) standards for minimum dietary diversity. Anthropometric failure was constructed using the WHO child growth reference standard z-score for stunting, underweight and wasting. We cross-tabulated dietary and anthropometric failures yielding four potential outcomes: Dietary Failure Only (DFO), Anthropometric Failure Only (AFO), Both Failures (BF), and Neither Failure (NF). Of the 162,589 children in our sample, 42.9% of children had dietary failure according to the standard WHO definition without being identified as having anthropometric failures. We found 34.7% BF, 42.9% DFO, 8.3% AFO, and 14.1% NF. Dietary and anthropometric measures were discordant for 51.2% of children; these children had nutritional needs identified by only one of the two measures. The results were consistent across geographical regions. We conclude that the current standard of measuring child undernutrition with prevalence of anthropometric failure should be complemented with diet- *and* food-based measures, as anthropometry alone fails to identify many children that suffer from insufficient dietary intake.

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II.1 Introduction

Child undernutrition is a significant burden across the globe, with WHO estimates reporting more than 205 million children being undernourished, particularly in low- and middle-income countries (LMICs).[1] Undernutrition in early childhood has been linked to significant harm in physical as well as cognitive development.[2-5] As such, preventing and treating child undernutrition is not only relevant to achieve the Sustainable Development Goal (SDG) on “Good Health and Well-being” but also to address root causes of health inequality.

There are two measures relevant when looking at children’s nutrition: anthropometry and diet. While both measures are relevant, scientific research and policy agenda most often rely on anthropometry, more specifically anthropometric failures, when determining the degree and magnitude of undernourishment among children.[6,7] A child is considered to have anthropometric failure if it is either stunted, underweight, wasted or a combination of the three. Anthropometric failure is an important measure that is closely related to food and often leads to targeted nutrition-based interventions.[8,9] At the same time, it is a fairly complex indicator capturing genetic, environmental and household factors as well.[10] This means that anthropometric failure may occur even when nutrition intake is generally sufficient. Similarly, not all nutritional deficiencies would be expected to result in anthropometric failure.[11] Thus, while anthropometric failure hints towards undernutrition, it is an imprecise measure to determine the full extent of the under- and malnutrition and to identify precise target groups for nutrition interventions.[12-15]

To examine the association between the prevalence of diet and anthropometric failure, Beckermann-Hsu et al. (2020) recently established a typology framework consisting of four “Dietary and Anthropometric Failure” (DAF) categories: Dietary Failure Only (DFO), Anthropometric Failure Only (AFO), Both Failures (BF), and Neither Failure (NF) (Table 1).[13] Using Indian DHS data to assign children into these four categories, they found that 36.3% of children suffered from micronutrient deficiency without showing any sign of anthropometric failure. Including those children that also showed signs of anthropometric failure, more than 80.3% of children did not meet the WHO standard for minimum acceptable diet (compared to 53.8% showing signs of anthropometric failure only). By using this newly proposed typology, this study showed that considering anthropometric failure only to determine the extent of undernutrition does not capture the full burden and that many children with insufficient micronutrient intake remain “hidden”, leading to imprecise target groups for nutrition interventions. This also has important implications for policymakers, for example, when it comes to allocating budgets for targeted interventions.

Table II.1: Four different "Dietary and Anthropometric Failure" (DAF) categories as defined by Beckermann-Hsu et al.(2020)- Replicated results for India

DAF Category	Sample Size India	% population India	95% Conf. Interval
BF: Both Failures	28,867	44.9%	[44.5%;45.3%]
DFO: Dietary Failure Only	23,906	35.8%	[35.4%;36.2%]
AFO. Anthro. Failure Only	6,294	9.9%	[9.7%;10.1%]
NF: Neither Failure	6,430	9.4%	[9.2%;9.6%]

Given that Beckermann-Hsu et al's sample was restricted to India, there is a need to apply the "Dietary and Anthropometric Failure" (DAF) framework to a larger cross-country sample. If the results presented for India can be validated for a global sample, it becomes clear that measures of diet and micronutrient intake need to be much more prevalent in future research on child undernutrition. Doing so has two potential benefits. At first, it can help to identify children with nutritional needs that were previously undetected, giving more precise target groups and estimates of the true extent of child undernutrition. A second advantage of incorporating dietary intake is the potential identification of the precise food-based needs (i.e., which micronutrients are missing) that enables policymakers to make evidence-based prioritization for resource allocation and to monitor progress of respective interventions at both national and global levels.

In this paper, we extend the "Dietary and Anthropometric Failure" (DAF) framework introduced by Beckermann-Hsu et al.[2] to a total of 55 LMICs for which DHS data was available. We calculate country-specific typology patterns and derive an estimate of the magnitude of the true burden caused by anthropometric failure and micronutrient deficiency together among 6-23 months old children. By doing so, we show the global discordance i.e., children having a dietary but not anthropometric failure, or vice versa, between dietary and anthropometric failures, and estimate how many children may be overlooked if the global health community continues to assess child undernutrition by anthropometric failure alone.

II.2 Methods

Data

The Demographic Health Survey (DHS) program conducts survey waves on population, health, and nutrition for nationally representative samples across the globe. Households are chosen in a two-stage process first selecting enumeration areas and then, in a second step, sampling households for each enumeration area. Verbal informed consent is sought from respondents by reading a prescribed statement to the respondent and recording in the questionnaire whether the respondent consented. For each country, we leveraged the most recent DHS survey wave, which was conducted after 2009 (therefore including data from the past 10 years) that contained both information on children's dietary intake, height and weight measurements, as well as month-specific age information. These surveys were available for 55 countries. For Colombia, we used the DHS Wave 6 data from 2010 instead of Wave 7 data from 2015, as it contained many more data points on nutrition relevant to our analyses. We also used population data drawn from the United Nations World Population Prospect (2018) to estimate the total child population counts corresponding to each DAF type.[16] As such, the largest seven countries considering children aged 6-23 months (i.e., India, Nigeria, Pakistan, Democratic Republic of Congo, Bangladesh, Ethiopia and Egypt) contribute ~66% of the total sample of 55 countries. Mean per capita income information was drawn from PovCalNet, UNU-WIDER and Human Development Reports.

Study Population and Sample Size

Our analyses included children aged between 6-23 months (subsequently referred to as "children"), which is in line with the WHO Indicators for assessing infant and young feeding practices (ICYF).[17] We attained nationally representative DHS data from 55 LMICs for 208,044 children between 6-23 months of age that were the youngest child in the household and that lived together with their mother.[18] Out of our sample of 208,020 children, 166,929 children had height and weight measurements used to derive the z-scores to identify anthropometric failure. Out of these, 162,589 had dietary data, yielding our final sample size of 162,589. Out of these, 48.7% were female, and 35.0% were aged between 6-11 months, and 65.0% were aged 12-23 months (Supplement Figure1).

Outcomes

Anthropometric failure

Children's anthropometry data (measured height and weight) were attained from the DHS data. The WHO child growth reference standard z-score was used to identify children with stunting (height-for-age z-score<-2), underweight (weight-for-age z-score<-2) and wasting (weight-for-height z-score<-2). Anthropometric failure was defined as a binary variable with anthropometric failure prevailing if a child was either stunted, underweight, wasted or a combination of these failures.

Dietary failure

Children's dietary data were based on a 24h recall in the DHS surveys. Children's consumption of the following eight food groups were collected: 1. Grains, roots and tubers, 2. Legumes and nuts, 3. Dairy products (milk, yogurt, cheese), 4. Flesh foods (meat, fish, poultry and liver/organ meats), 5. Eggs, 6. Vitamin-A-rich fruits, 7. Vegetables, and 8. Breastmilk. We defined dietary failure as a binary variable, assigning outcome "Yes" if the child's dietary intake did not meet the minimum dietary requirements as defined by the WHO classification from 2017, requiring an intake of a minimum of 5 out of 8 different food categories.[17] As recommended by DHS,[18] for all food categories answers such as "don't know" or individual missing data points were assumed to be a "No". Given our sample of ~200k responses for each food category and an average of ~350 responses being either "don't know" or missing data points, we do not believe that assigning these missing 0.2% to "No" significantly impacts our results. The indicator for minimum dietary diversity was created as a way to use dietary data to capture the micronutrient density of the diets in children 6–23 months old and has been validated previously.[19,20] Hence, children not reaching the minimum dietary diversity can be considered as having unmet nutritional needs, regardless of prevailing anthropometric failure or not.

Statistical Analyses

We cross-tabulated anthropometric and dietary failures yielding four potential outcomes: Dietary Failure Only (DFO), Anthropometric Failure Only (AFO), Both Failures (BF), and Neither Failure (NF). We calculated the prevalence of dietary and anthropometric failures and for each respective DAF category on national levels for all 55 LMICS. Additionally, we estimated the burden, in terms of total headcount, of each DAF category using UN population data from 2018 for 0-5-year-old children in these 55 countries. Given that DHS is a nationally representative dataset, we extrapolated the share of children aged 6-23 months (30.3%) from children aged 0-5 years (N=357.0 million) to the national population estimates according to the UN, yielding our final population size (N=106.9 million) of children aged 6-23 months for the 55 countries included in our analysis. We considered 5% levels of significance and hypothesis tests were two-sided. All analyses were conducted on Stata version 16.0. This analysis was reviewed by the Harvard T.H. Chan School of Public Health Institutional Review Board and was considered exempt from full review as the study was based on an anonymous public dataset.

II.3 Results

Overall child undernutrition using DAF categories

Across all 55 LMICs and weighted by country size, 77.6% of a sample of 162,589 children aged 6-23 months children were shown to have dietary failure, while only 43.0% had at least one form of anthropometric failure. The most common category was DFO for 42.9% of children, followed by BF with 34.7%, NF with 14.1% and AFO 8.3% (Table 2). The overall discordance was 51.2% (DFO+AFO) of the total population. While these results are strongly influenced by India, which accounts for roughly one-third of the total child population in our final sample, the results did not change significantly for DFO when we considered unweighted averages (DFO: 45.9%, BF: 26.4%, NF: 19.7%, AFO: 8.1%) (Supplement Table 1). Using the weighted prevalence of DAF in Table 2, we estimated the total headcount of children in different categories of DAF: DFO was the largest category with an estimated population of 45.3 million children, followed by BF with 36.7 million children, NF with 14.9 million children, and AFO with 8.8 million children (Table 2). A more granular look at the prevalence of dietary failure and the prevalence of individual causes of anthropometric failure, i.e., stunting, wasting and underweight, can be found in Supplement Table 2.

Table II.2: Estimated prevalence of children within DAF type in our sample of 6-23 months children in 55 countries

DAF Category	Sample Size	Est. Child Population (mn)	Percentage*	95% Conf. Interval
Both Failures	55,194	36.7	34.7%	[34.5%;35.0%]
Dietary Failure Only	67,670	45.3	42.9%	[42.6%;43.1%]
Anthropometric Failure Only	14,432	8.8	8.3%	[8.2%;8.4%]
Neither Failure	25,293	14.9	14.1%	[14.0%;14.3%]
Total	162,589	105.8		

*Percentage weighted by country's child population

Country-specific analysis of DAF

Figure 1 shows country-specific estimates for the prevalence of the DAF categories together with estimated population headcounts. A certain degree of variation in the share of each DAF category was found for different countries. While the Maldives (51.5%) and Peru (57.2%) had fairly large share of children with NF, Niger (53.6%), Burkina Faso (47.9%), and Burundi (47.6%) had BF for roughly half of their child population between 6-23 months. Gabon (66.2%), Haiti (62.6%) and Liberia (60.9%) had large shares of DFO category, which captures children with nutritional needs that are missed looking at anthropometric measures only. At the same time, the overall message remains unchanged. For a total of 41 out of the 55 LMICs, DFO was the largest category. For 38 out of the 55 LMICs, at least 40% of children fell in the DFO category, further highlighting the importance of capturing nutritional intake in addition to anthropometric failure. In terms of the total headcount of children with DFO, the largest eight countries contributed ~66.7% to the total headcount of children with DFO. Out of those, India was the largest by far, contributing 28.0% to the total DFO headcount (Figure 1).

DAF by geographic regions and country level income

The level of a country's share of children within DFO seems to be consistent across different geographic regions and income levels. While NF and BF shares vary quite a lot, DFO accounts for the majority of children in all geographic regions ranging from ~35% of children in Middle- and South America to ~50% in Europe (i.e. Albania and Armenia) (Table 3). Finally, country-level income levels (measured as mean annual household income per capita) also do not seem to have a significant influence on the share of children with DFO (Figure 2). While the prevalence of BF and NF were significantly related to a country's income level, DFO was correlated at a 10% level of significance and AFO had no significant relationship with a country's income level. Supplement Figure 2 additionally shows the distribution of DAF category shares for different mean income per capita levels.

Figure II.1: Share (%) and estimated child population for each of the DAF categories across 55 countries

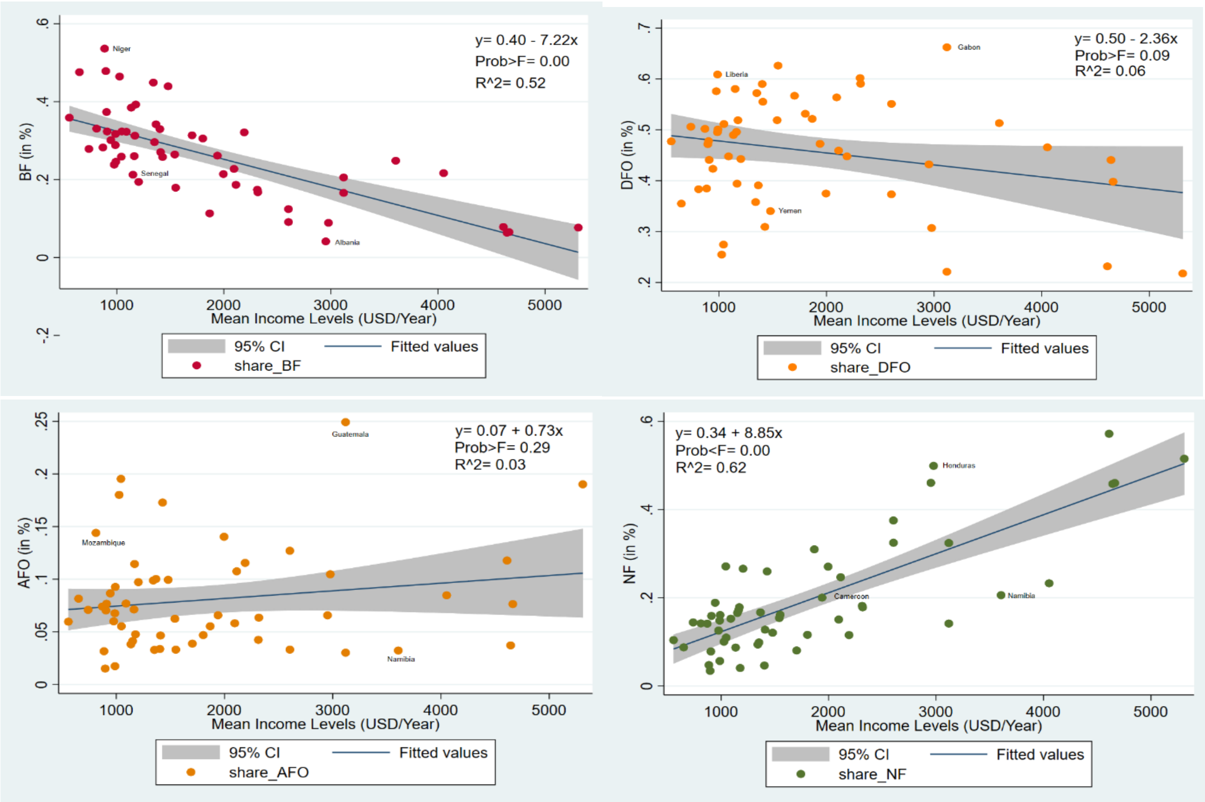
	# Children Based on Total Population (in '000)					DAF Category Share				
Countries	BF	DFO	AFO	NF	Total	BF	DFO	AFO	NF	Share Total DFO Burde
India	15,938	12,706	3,507	3,338	35,489	44.9%	35.8%	9.9%	9.4%	28.0%
Nigeria	2,897	3,949	687	1,423	8,957	32.3%	44.1%	7.7%	15.9%	8.7%
Pakistan	2,216	3,856	341	842	7,254	30.5%	53.2%	4.7%	11.6%	8.5%
Congo Democratic Republic	1,684	2,239	280	488	4,690	35.9%	47.7%	6.0%	10.4%	4.9%
Ethiopia	1,758	2,238	175	398	4,568	38.5%	49.0%	3.8%	8.7%	4.9%
Egypt	795	1,956	458	1,050	4,259	18.7%	45.9%	10.8%	24.7%	4.3%
Bangladesh	1,597	1,826	468	780	4,671	34.2%	39.1%	10.0%	16.7%	4.0%
Tanzania	838	1,438	197	431	2,903	28.9%	49.5%	6.8%	14.8%	3.2%
Uganda	570	1,086	156	378	2,190	26.0%	49.6%	7.1%	17.2%	2.4%
Kenya	423	964	212	579	2,177	19.4%	44.3%	9.7%	26.6%	2.1%
Cote d'Ivoire	447	800	46	63	1,355	33.0%	59.0%	3.4%	4.6%	1.8%
Myanmar	315	781	81	209	1,385	22.7%	56.4%	5.8%	15.1%	1.7%
Ghana	221	778	84	235	1,318	16.8%	59.1%	6.4%	17.8%	1.7%
South Africa	353	759	138	379	1,629	21.7%	46.6%	8.5%	23.3%	1.7%
Cameroon	361	653	91	277	1,381	26.1%	47.2%	6.6%	20.0%	1.4%
Mozambique	556	644	242	239	1,681	33.1%	38.3%	14.4%	14.2%	1.4%
Angola	511	644	187	292	1,634	31.3%	39.4%	11.4%	17.9%	1.4%
Mali	286	509	75	143	1,013	28.3%	50.2%	7.4%	14.1%	1.1%
Niger	684	490	40	60	1,275	53.6%	38.5%	3.2%	4.7%	1.1%
Burkina Faso	488	481	15	35	1,019	47.9%	47.2%	1.5%	3.4%	1.1%
Colombia	74	452	87	523	1,136	6.5%	39.8%	7.6%	46.0%	1.0%
Senegal	162	444	32	127	764	21.3%	58.0%	4.1%	16.6%	1.0%
Chad	322	425	39	33	819	39.3%	51.9%	4.8%	4.1%	0.9%
Yemen	542	420	123	149	1,234	44.0%	34.0%	9.9%	12.1%	0.9%
Malawi	224	406	57	116	803	27.9%	50.6%	7.1%	14.4%	0.9%
Zambia	265	368	63	125	821	32.3%	44.8%	7.7%	15.3%	0.8%
Zimbabwe	162	318	38	94	612	26.4%	51.9%	6.2%	15.4%	0.7%
Benin	134	273	51	88	546	24.6%	50.1%	9.3%	16.1%	0.6%
Guinea	164	259	28	56	507	32.3%	51.2%	5.5%	11.0%	0.6%
Nepal	213	255	142	214	824	25.8%	30.9%	17.3%	26.0%	0.6%
Rwanda	177	248	51	111	586	30.1%	42.3%	8.7%	18.9%	0.5%
Tajikistan	72	248	17	75	411	17.4%	60.2%	4.2%	18.2%	0.5%
Togo	96	232	24	51	403	23.8%	57.6%	6.0%	12.6%	0.5%
Cambodia	122	213	80	154	567	21.4%	37.5%	14.0%	27.1%	0.5%
Haiti	61	212	11	55	339	17.9%	62.6%	3.3%	16.1%	0.5%
Burundi	284	212	49	52	598	47.6%	35.5%	8.2%	8.8%	0.5%
Peru	66	194	98	478	835	7.8%	23.2%	11.8%	57.2%	0.4%
Sierra Leone	138	176	26	29	369	37.3%	47.8%	7.0%	7.8%	0.4%
Liberia	81	155	4	14	254	31.7%	60.9%	1.7%	5.7%	0.3%
Congo	75	154	13	35	278	27.1%	55.5%	4.7%	12.8%	0.3%
Dominican Republic	21	142	12	148	323	6.4%	44.1%	3.7%	45.8%	0.3%
Kyrgyz Republic	30	138	15	82	265	11.3%	52.2%	5.5%	31.0%	0.3%
Guatemala	127	137	154	200	618	20.6%	22.1%	24.9%	32.4%	0.3%
Honduras	29	100	34	162	324	8.9%	30.7%	10.5%	49.9%	0.2%
Gambia	41	75	5	11	132	31.4%	56.7%	3.9%	8.0%	0.2%
Gabon	17	69	3	15	105	16.6%	66.2%	3.0%	14.2%	0.2%
Namibia	29	60	4	24	117	24.8%	51.3%	3.2%	20.6%	0.1%
Lesotho	26	50	3	9	87	29.6%	57.2%	3.3%	9.9%	0.1%
Armenia	6	36	2	21	66	9.1%	55.1%	3.3%	32.5%	0.1%
Albania	2	22	3	24	52	4.1%	43.2%	6.6%	46.1%	0.0%
Comoros	13	18	5	5	39	32.1%	44.8%	11.6%	11.5%	0.0%
Timor-Leste	23	13	9	5	50	46.5%	25.5%	18.0%	10.0%	0.0%
Guyana	3	8	3	9	23	12.4%	37.3%	12.7%	37.5%	0.0%
Sao Tome and Principe	3	3	2	3	10	25.9%	27.4%	19.5%	27.1%	0.0%
Maldives	1	2	2	5	11	7.7%	21.8%	19.0%	51.5%	0.0%
Total (Weighted)*	**36,738**	**45,333**	**8,769**	**14,937**	**105,778**	**34.7%**	**42.9%**	**8.3%**	**14.1%**	**100%**
Total (Unweighted)**						**26.4%**	**45.9%**	**8.1%**	**19.7%**	

** Weighted by Pop Weights AND Country Size*

*** Weighted by Pop Weights BUT NOT Country Size*

DAF categories: Dietary Failure Only (DFO), Anthropometric Failure Only (AFO), Both Failures (BF), and Neither Failure (NF). Shadings categorize DAF shares into different intensity categories, ranging from green for low shares to red for the higher shares.

Figure II.2: Correlation between country-level mean income p.c. and DAF category share



DAF categories: Dietary Failure Only (DFO), Anthropometric Failure Only (AFO), Both Failures (BF), and Neither Failure (NF). The gray shaded area indicates 95% confidence intervals, colored dots, survey results for individual nations in the data set

Table II.3: Share of four DAF types across geographic regions in Europe, Asia, Africa and South America

Region	**A. Asia**	**B. Africa**
DAF Category Shares [95% Confidence Intervals]	Both Failures 40.4% [40.0%;40.7%] Dietary Failure Only 39.2% [38.9%;39.6%] Anthropometric Failure Only 9.2% [9.0%;9.4%] Neither Failure 11.2 % [11.0%;11.4%]	Both Failures 30.6% [30.3%;31.0%] Dietary Failure Only 47.2% [46.8%;47.6%] Anthropometric Failure Only 7.2% [7.0%;7.4%] Neither Failure 15.0% [14.7%;15.2%]
# countries in sample	9	37
Sample size	78.694	65.483

Total estimated child population (6-23mths)	52.1 million	50.0 million
Region	**C. South America**	**D. Europe**
DAF Category Shares [95% Confidence Intervals]	Both Failures 10.5% [10.1%;11.0%] Dietary Failure Only 34.6% [33.9%;35.3%] Anthropometric Failure Only 11.1% [10.6%;11.6%] Neither Failure 43.8% [43.0%;44.5%]	Both Failures 6.9% [5.4%;8.4%] Dietary Failure Only 49.9% [47.0%;52.7%] Anthropometric Failure Only 4.8% [3.5%;6.0%] Neither Failure 38.5 % [35.7.0%;41.3%]
# countries in sample	7	2
Sample size	17.059	1.153
Total estimated child population (6-23mths)	3.6 million	117.3 thousand

DAF categories: Dietary Failure Only (DFO), Anthropometric Failure Only (AFO), Both Failures (BF), and Neither Failure (NF)

Variation within DAF

It is possible that these findings are explained by certain patterns within the DAF categories. Given that we examined children between 6 – 23 months varying age patterns within the DAF categories could explain our results, e.g. it may take time for anthropometric failure to manifest and thus, BF children being older than DFO children. At the same time, certain food groups may be explanatory for the allocation into the respective DAF categories, e.g. certain food groups being responsible for DFO, AFO and BF. Looking at these two factors serves as robustness check to our findings.

Supplement Table 3 shows the average age in months for each of the DAF categories across the region. Indeed, AFO has the oldest average age in months across all regions and DFO has the lowest average age in three of the four regions. However, comparing particularly the differences between DFO and BF (as both have dietary failure and thus are a better comparison than DFO and AFO), the variation is moderate between -0.1 to + 1.7 months of average age.

Supplement Figures 3.1 and 3.2 present the variation of average consumption level of the previously mentioned eight different food groups both for the whole sample and for each region. At first, it is noteworthy that average consumption patterns for each of the food groups are similar for both categories without dietary failure (AFO and NF) as well as with dietary failure (DFO and BF). This implies that there is not a certain micronutrient responsible for anthropometric failure. Secondly, there is a set of food groups that are most relevant for causing dietary failure. Average consumption levels are particularly low for 2. Legumes and nuts, 4. Flesh foods, 5. Eggs and 7. Vegetables. Overall, while certain groups are more responsible for causing dietary failure, there is no indication that certain micronutrients cause anthropometric failure further indicating that micronutrient intake should be examined next to anthropometric failure to capture nutrition deficiencies.

II.4 Discussion

Our study has a number of salient findings. First, over roughly four out of ten children in our analytic sample of 55 LMICs had no anthropometric failures but were identified as having dietary failure ("DFO" category) amounting to more than 45 million children aged 6-23 months with unmet dietary needs who are currently not identified by measures focused solely on anthropometry. Second, about a third of children had both dietary and anthropometric failures and roughly four out of five children did not meet the minimum dietary diversity as recommended by WHO, underscoring the depth of nutritional need among a large proportion of global child population in developing countries. Finally, while there is some variation across countries, the relevance of the DFO category is consistent across different geographical regions and country-level mean income as is within-category variation of age and food group consumption.

Future research will be needed to identify improved ways of measuring dietary intake, ideally over a longer period of time to cater for volatility in 24h food intake. We leveraged the WHO minimum dietary diversity indicator, but other dietary indicators may be thought of, that combine the cost effectiveness of a survey question (rather than relying on biomedical information and medical examinations) with increased reliability over time and sensitivity.[21] Similarly, given varying degrees of nutritional intake at different stages in early childhood, other/additional indicators may be considered for different age groups. Given that Beckermann-Hsu et al. (2020) found larger variations of the DAF categories at the district level in India future research will also need to take a more granular look into county and district level DAF prevalence to properly choose and prioritize food policy interventions.

The fact that DFO is a major category across geographic regions and country-level income, underscores the need to consider dietary intake alongside anthropometric failure in determining the extent of nutritional burden in a more comprehensive manner and to successfully address food security across the globe. We acknowledge that anthropometric failure is an important measure that is closely related to nutrition and often leads to targeted interventions that include providing food to the children in need.[8,9] We therefore do not intend to argue for a replacement or substitution of anthropometric failure in global health research and policy. Instead, we provide empirical evidence indicating that considering anthropometric failures alone may leave large parts of the population with nutritional deficiencies undetected. Across the 55 LMICs considered in our analysis, this translates to more than 45 million children who appeared to be normal based on anthropometry measures but in fact were in need of better nutrition. Complementary analysis considering dietary intake together with anthropometric failure enables more precise identification of children with nutritional needs and may facilitate policymakers to develop more effective, equitable and targeted interventions that could increase global food security.

Limitations

There are two sources of data limitations. First, given that the dietary data were self-reported by mothers based on a 24h recall, the innate nature of the data is subject to some measurement error. However DHS data on dietary intake has been found to be appropriate for population-level.[22] Second, our estimates may be biased by survey non-response and missing data for specific survey items or countries. However, given that we attained complete nutrition and anthropometric data for an average of ~80% of all children in the sample for 55 out of the 60 countries that conducted the standard DHS surveys in the past 10 years (Afghanistan, Philippines, Jordan, Indonesia, Madagascar missing), any bias is expected to be small.

II.5 Conclusion

The current standard of measuring child undernutrition should be complemented with diet- *and* food-based measures, as anthropometry alone fails to identify many children that suffer from insufficient dietary intake. Like anthropometric failure, dietary diversity and micronutrient intake needs to be considered both as a key policy outcome and a metric in scientific research.

II.6 Appendix

Supplement Table II.1: Estimated prevalence of children within DAF type in our sample of 6-23 months children in 55 countries

DAF Category	Sample Size	Percentage*	95% Conf. Interval
Both Failures	55,194	26.4%	[26.2%;26.6%]
Dietary Failure Only	67,670	45.9%	[45.6%;46.1%]
Anthropometric Failure Only	14,432	8.1%	[7.9%;8.2%]
Neither Failure	25,293	19.7%	[19.5%;19.9%]
Total	162,589		

*Equal weighting for each country

Supplement Table II.2: Prevalence of dietary failure in relationship with the prevalence of the three different types of anthropometric failure for our sample of 6-23 months children in 55 countries

		Wasting		**Stunting**		**Underweight**	
		Presence	Absence	Presence	Absence	Presence	Absence
Dietary Failure	Presence	20,094 12.4%	102,770 63.2%	39,372 24.2%	83,492 51.3%	30,061 18.5%	92,803 57.1%
	Absence	4,146 2.6%	35,579 21.9%	11,134 6.9%	28,591 17.6%	6,498 4.0%	33,227 20.4%
Total		24,240 14.9%	138,349 85.1%	50,506 31.1%	112,083 68.9%	36,559 22.5%	126,030 77.5%
Discordance		65.8%		58.2%		61.1%	

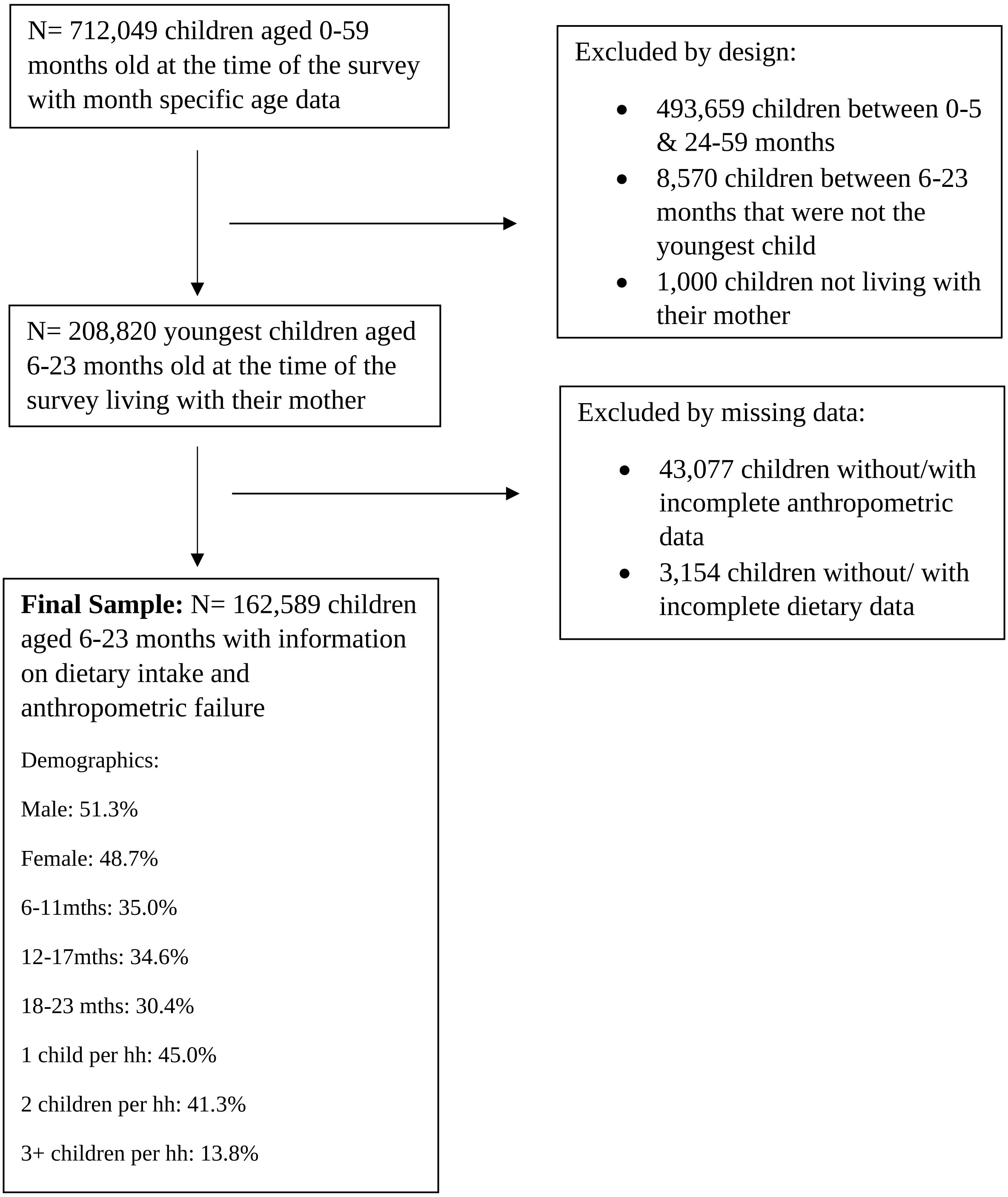
Numbers are sample size and percentages weighted by country size

Supplement Table II.3: Average age in months of children in respective DAF categories.

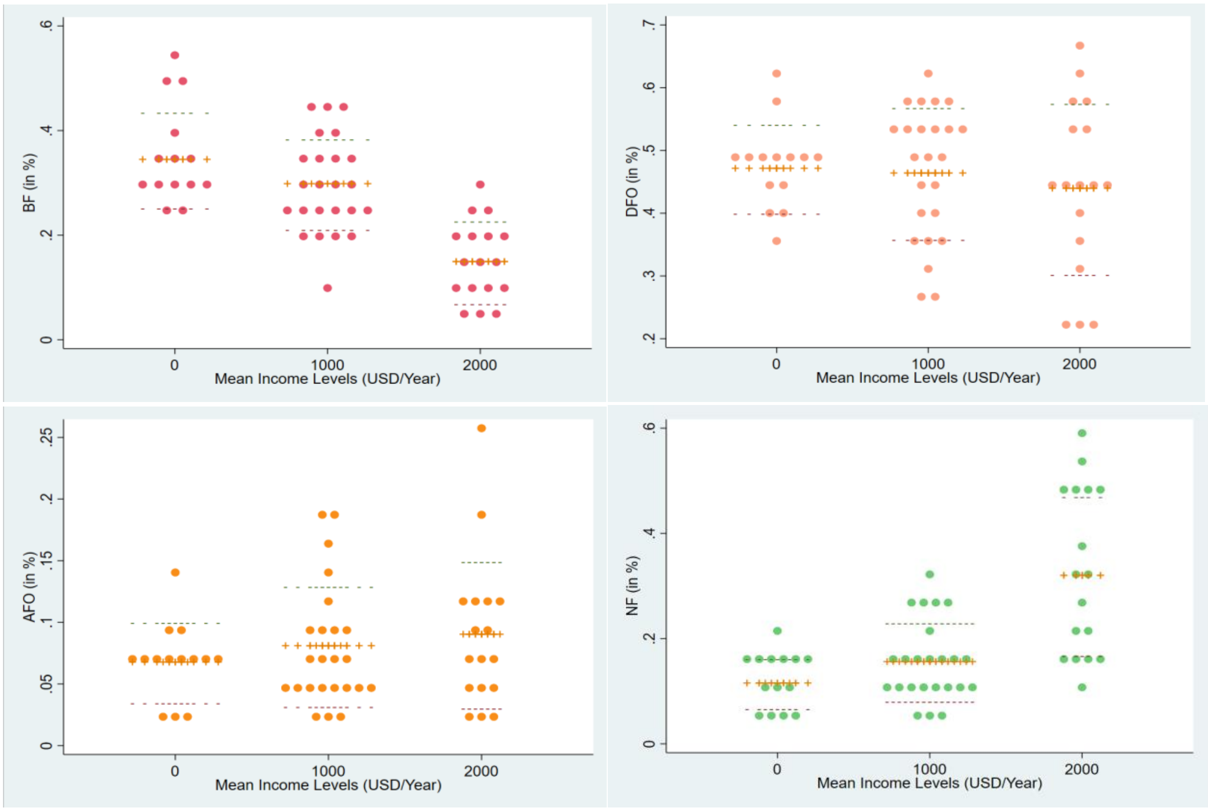
	Both Failures	**Dietary Failure Only**	**Anthropometric Failure Only**	**Neither Failure**
Africa	14.8	13.1	*15.7*	14.6
Asia	14.3	13.0	*16.6*	15.8
Europe	13.2	13.3	*15.6*	15.4
South America	14.6	13.1	*16.0*	14.8

The Italic values are the oldest average age of DAF categories per region; the underscored values are the lowest average age of DAF categories per region

Supplement Figure II.1: Flow diagram showing exclusions, missing data and final sample size of the study population



Supplement Figure II.2: Distribution of children in DAF groups for different mean income per capita levels across 55 countries



DAF categories: Dietary Failure Only (DFO), Anthropometric Failure Only (AFO), Both Failures (BF), and Neither Failure (NF). The colored dots indicate survey results for individual nations in the data set, the pluses are the mean value for each Income Group and the grey dotted lines indicate the range of the mean plus and minus the standard deviation.

Supplement Figure II.3.a: Global prevalence of food groups as recommended by WHO per child in the respective DAF categories

DAF Category	Grains, roots and tubers	Legumes and nuts	Dairy products	Flesh foods	Eggs	Vitamin A rich foods	Vege-tables	Breastmilk
AFO	97.9%	53.2%	68.1%	58.9%	52.8%	86.5%	70.6%	83.8%
BF	69.7%	10.5%	32.6%	13.7%	7.3%	31.3%	10.3%	81.4%
DFO	70.1%	10.5%	34.8%	18.5%	9.3%	29.3%	12.2%	78.2%
NF	98.0%	50.8%	73.1%	66.2%	55.0%	82.4%	67.6%	77.3%

DAF categories: Dietary Failure Only (DFO), Anthropometric Failure Only (AFO), Both Failures (BF), and Neither Failure (NF). The shadings categorize average consumption levels different intensity categories, ranging from green for low levels to red for the higher levels.

Supplement Figure II.3.b: Regional prevalence of food groups as recommended by WHO per child in the respective DAF categories

region	DAF Category	Grains, roots and tubers	Legumes and nuts	Dairy products	Flesh foods	Eggs	Vitamin A rich foods	Vege-tables	Breastmilk
Africa	**AFO**	97.3%	60.3%	56.3%	77.1%	45.5%	85.0%	66.2%	79.5%
	BF	72.5%	17.0%	18.8%	24.2%	6.9%	37.9%	9.1%	78.6%
	DFO	71.5%	14.5%	24.1%	27.2%	7.7%	34.7%	10.8%	77.2%
	NF	97.6%	55.9%	66.6%	74.7%	49.2%	83.5%	63.2%	75.7%
Asia	**AFO**	98.2%	47.0%	77.3%	44.2%	56.9%	88.8%	74.1%	87.8%
	BF	67.5%	5.3%	42.8%	5.8%	7.4%	26.6%	10.9%	83.7%
	DFO	67.8%	5.1%	45.9%	7.6%	10.5%	23.2%	13.1%	80.6%
	NF	98.2%	43.1%	79.9%	52.0%	60.0%	83.0%	72.7%	82.3%
Europe	**AFO**	97.8%	41.2%	96.8%	74.5%	69.5%	79.8%	76.3%	45.6%
	BF	71.8%	6.2%	66.2%	21.5%	17.1%	20.2%	49.2%	46.1%
	DFO	76.1%	1.8%	63.6%	21.3%	16.1%	28.9%	46.3%	48.2%
	NF	98.4%	39.7%	94.5%	81.2%	58.9%	80.1%	88.4%	51.2%
South America	**AFO**	98.7%	64.4%	64.3%	70.1%	69.2%	73.4%	69.1%	74.9%
	BF	80.6%	32.9%	31.9%	26.2%	21.2%	27.3%	20.3%	64.6%
	DFO	81.6%	24.6%	52.3%	30.5%	18.4%	27.9%	20.9%	56.6%
	NF	98.9%	55.9%	78.3%	77.8%	63.9%	75.5%	69.1%	67.2%

DAF categories: Dietary Failure Only (DFO), Anthropometric Failure Only (AFO), Both Failures (BF), and Neither Failure (NF). The shadings categorize average consumption levels different intensity categories, ranging from green for low levels to red for the higher levels.

Chapter III

Food group consumption patterns among children meeting and not meeting WHO's recommended dietary diversity: Evidence from 197,514 Children in 59 countries

With: Rockli Kim, Smriti Scharma, Sebastian Vollmer and S.V. Subramanian

Abstract

The minimum dietary diversity (MDD) indicator as defined by the WHO is commonly used to assess micronutrient deficiency in young children. However, individual food item-specific consumption patterns may be overlooked when focusing solely on this indicator. We provide a comprehensive view on food item and food group consumption patterns of children aged 6-23 months old using DHS data from 59 low- and middle-income countries. Consumption levels of food items ranged from 79.0% for breastfeeding to 5.9% for organ meats, showing particularly low levels for protein rich food items. There were significant differences in food item consumption levels for different countries as well as household correlates' relevance such as a household's wealth decile and the child's age group, hinting towards potential underlying mechanisms such as regional availability, household's available resources and awareness of food group's importance from early age. The results suggest that the analysis of MDD should be complemented with information on individual food item consumption to identify priorities for policymakers aiming to fight undernutrition across the globe.

Study published in: Food Policy 112 (2022): doi: 10.1016/j.foodpol.2022.102368

III.1 Introduction

Child undernutrition is a significant burden across the globe, which has been linked to significant harm in physical as well as cognitive development.[1-4] According to WHO estimates, more than 205 million children are undernourished, most of them living in low- and middle-income countries (LMICs).[5] There are two measures commonly used in research to assess children's nutrition: anthropometry and diet.[6] Anthropometry is classified as showing signs of body measurement failure (i.e. being stunted, wasted or underweight). To measure micronutrient density of the diet of young children, researchers often consider WHO's recommended criteria for meeting minimum dietary diversity (MDD).[7]

Minimum dietary diversity (MDD) was first defined in 2008 by WHO to track the micronutrient density of children's diet between 6 and 23 months. Together with Minimum Meal Frequency (MMF) and Minimum Adequate Diet (MAD), these indicators allow policymakers to compare feeding practices over place and time, identify nutrition needs and thus, allowing to target interventions and to monitor progress and evaluate interventions' effects on children's nutrition. According to WHO, starting at six months of age, breastmilk alone does not provide sufficient nutrients for a child anymore and appropriate complementary feeding should start with continued breastfeeding up to two years or beyond.[8] This age is considered a "critical window", in which poor nutrition has direct consequences of increased morbidity and mortality and delayed development of the brain and the nervous system.[9,10] The MDD in its current form contains 8 food groups (that themselves are composed of different food items) for which a MDD was achieved if a child consumed >=5 of these food groups in the previous day or night.[7]

It has been shown that diet and specifically MDD does not have strong overlaps with anthropometric failure and that, only focusing on anthropometry fails to identify a large share of children in LMICs with unmet nutritional needs.[6] It is therefore argued that food consumption itself needs to be considered a key outcome of interest next to anthropometry when determining child undernutrition across the globe. However, food consumption patterns beyond the question of whether MDD was met have not been studied extensively yet, particularly on a food item level and across multiple LMICs.

For policymakers this carries important insights: What is the variation of food item consumption behind the tracked food groups? Which food groups are responsible for separating children who meet MDD and those who do not? And is it possible to infer root causes for varying consumption levels for different food items/groups? To answer these questions, one needs to look past the binary outcome of MDD or the consumption of a certain food group and include food item analysis to truly compare feeding practices, identify needs and monitor progress. If there is little variation, there would be no need to look beyond food groups and MDD, however previous research from India on a food group level suggest otherwise.[11]

As such we aim to add to the literature in two distinct ways. Our first contribution is to compare food group consumption patterns in a total of 59 low- and middle-income countries. Second, we look behind the metrics of MDD and food group consumption by investigating food item-specific consumption patterns as well as item-specific socio-economic determinants. For our analyses, we used the most recent nationally representative data on children aged 6-23 months from 59 countries.

III.2 Materials and Methods

Empirical Application and Data

The Demographic Health Survey (DHS) program was established in 1984 to conduct surveys on population, health, and nutrition for nationally representative samples of women of reproductive age and thus also for small children in LMICs across the globe.[12] Households are chosen in a two-stage process, first selecting enumeration areas and then in a second step sampling households from each enumeration area. For each country in our sample, we leveraged the most recent DHS surveys which were conducted between 2009 and 2021 that contained information on children's dietary intake as well as month-specific age information. These surveys were available for 59 countries. For Colombia we used the DHS Wave 6 data from 2010 instead of Wave 7 data from 2015, as it contained many more data points on nutrition relevant for our analyses. We also used population data drawn from the United Nations World Population Prospect together with DHS estimates for age group population shares to determine the country-specific weight in our sample.

Study Population and Sample Size

Our analyses included children aged 6-23 months, as is recommended by the WHO Indicators for assessing infant and young child feeding practices (IYCF)[7]. We attained nationally representative DHS data from 59 LMICs for 203,614 children between 6-23 months of age that were alive at the time of the interview, that were the youngest child in the household and that lived together with their mother.[13] Out of this sample 197,514 had dietary data for each food group and 196,259 also had socio-economic household data. For five countries (Colombia, Guyana, Madagascar, Peru and Sao Tome & Principe) item-specific information for yogurt was not available as it was included in food item #7 cheese and other milk products. Additionally for Peru, data on food item “Fortified baby food” as well as food item “Organ meats” and “Fresh or dried fish/shellfish” was not available. Therefore, sample size for our regressions varied between 186,332 and 196,285 children aged 6-23mth depending on the specific food item (Supplement Figure 1). Based on child population estimates (0-5 years old) from the United Nations World Population Prospect, the full set of countries in our sample represents 63.1 percent of worldwide LMICs’ child population in that age group.

Variables of Interest- Minimal dietary diversity, food groups and food items

Children’s diet intake of a total of seventeen food items were collected as binary variables (consumption yes/no) based on a 24h recall in the DHS surveys. The seventeen food items were selected based on their allocation into the eight food groups defined by WHO which contain: #1 Grains, roots and tubers, #2 Legumes and nuts, #3 Dairy products (milk, yogurt, cheese), #4 Flesh foods (meat, fish, poultry and liver/organ meats), #5 Eggs, #6 Vitamin-A rich fruits and/or vegetables, #7 Any other fruits/vegetables and #8 Breastmilk (Figure 1). In addition, meeting the MDD was defined as a binary variable, assigning the outcome “Yes” if the child’s dietary intake met the minimum dietary requirements as defined by the WHO classification from 2017, requiring an intake of at least 5 out of 8 different food categories.[7] For all food items answers such as “don’t know” or individual missing data points within a food group were assumed to be a “No” as recommended by DHS.[13] This applied to less than 350 responses in our sample of around 200,000 observations.

Analyses

We calculated the consumption rates of the seventeen food items as well as the 8 food groups together with MDD prevalence for our whole samples well as individual countries and sub-populations. Additionally, we analyzed socio economic related consumption differences by running logit regressions for a set of socio-economic household characteristics on households’ food item consumption including survey fixed effects. The set of socio-economic household covariates included the child’s age in months, sex as well as the mother’s age at birth in years, maternal education level, relationship status, the household’s wealth quintile, and a dummy for urban households.

Figure III.1: DHS food items according to WHOs min. dietary diversity food group categories

Food Groups as considered by WHO	Food items collected by DHS
Food Group #1 **Grains, roots, tubers**	• Commercially fortified cereal (baby food) • Bread, rice, noodles, or foods made from grains • White potatoes, white yams, manioc, cassava, or any other foods made from roots
Food Group #2 **Legumes, nuts**	• Beans, peas, lentils, or nuts
Food Group #3 **Dairy**	• Powdered, tinned milk or fresh animal milk • Infant formula • Yogurt • Cheese or other milk products
Food Group #4 **Flesh Foods**	• Any meat (beef, pork, lamb, goat, chicken or duck) • Liver, heart, other organ meats • Fresh or dried fish or shellfish
Food Group #5 **Eggs**	• Eggs
Food Group #6 **Vitamin A-rich Fruits/Vegetables**	• Pumpkin, carrots, squash or sweet potatoes • Any dark green leafy vegetables • Ripe mangoes, papayas, other vitamin A fruit
Food Group #7 **Other Fruits/Vegetables**	• Other fruits or vegetables
Food Group #8 **Breastmilk**	• Currently breastfeeding

Additionally, we used chi-square tests for differences in consumption rate of the seventeen food items by children meeting MDD and those that did not. Given that DHS is a set of representative datasets, we extrapolated the share of children aged 6-23 months (29.1%) from children aged 0-5 years (N=377.3 million) to the national population estimates according to the UN yielding our final population size (N=109.8 million). This population size data for children aged 6-23 months was also used to assign each country an individual weight in our sample. Therefore, our weighted results are strongly influenced by the large population countries such as India (30.1%), Nigeria (8.2%), Indonesia (6.7%) and Pakistan (6.6%) together accounting for 51.5% of the total population size represented by our sample of children aged 6-23 months. We therefore also include results with equal country weights instead of population weights as robustness check. We present our results with 95% confidence intervals and include standard errors in brackets. All analyses were conducted with Stata version 16.0.

III.3 Results

Country-specific food item consumption levels

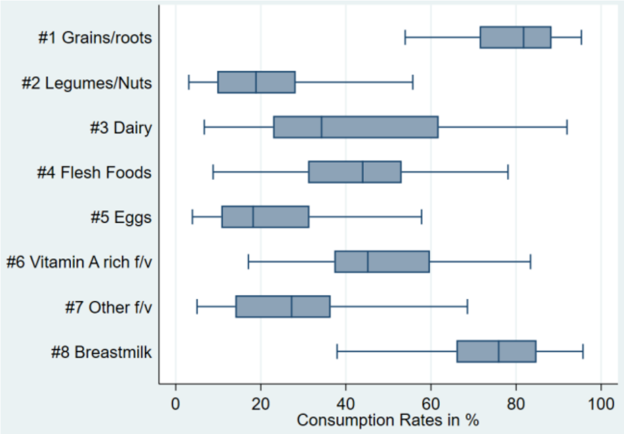
Across our full sample and weighted by country size, consumption levels for the eight different food groups were 79.0 (0.1)% for #8 Breastmilk, 76.9 (0.1)% for #1 Grains, 45.2 (0.1)% for #6 Vitamin A-rich Fruits/Veg., 43.1 (0.1)% for #3 Dairy, 30.2 (0.1)% for #4 Flesh Foods, 26.5 (0.1)% for #7 Other Fruits/Veg., 22.0 (0.1)% for #5 Eggs and 21.9 (0.1)% for #2 Legumes/Nuts (Table 1). This translated to 73.8 (0.1)% of 6-23 months old children not meeting MDD, i.e. consuming less than five food groups during the previous day and night of the interview underscoring the fact that in LMICs a large share of children had insufficient dietary variety. Looking at individual countries, we found large variation in average food group consumption levels as well as in overall levels of children reaching MDD. Overall intra-country variation was particularly high for food group #3 Dairy and lowest variation for food group #1 Grains (Figure 2a). More specifically, country-specific food-group consumption levels differed by up to 85.3 percentage points (pp.) for #3 Dairy, ranging from 92.0 (0.5)% in Jordan to 6.7 (0.4)% in Burundi), 73.3 pp. for #7 Other Fruits/Veg., 70.0 pp. for #2 Legumes/Nuts, 69.3 pp. for #4 Flesh Foods, 66.3 pp. for #6 Vitamin A-rich Fruits/Veg, 62.4 pp. for #8 Breastmilk, 53.9 pp. for #5 Eggs and 41.4 pp. for #1 Grains. Overall, our results showed particularly high inter-country differences for protein rich energy food groups.

Table III.1: Food group consumption levels, population and sample size per country for the eight food groups addressing WHO's MDD indicator

Country	Pop Size in '000 (6-23mth)	Sample Size	Grains	Legumes, nuts	Dairy	Flesh foods	Eggs	Vitamin-A-rich f/v	Other f/v	Breastfeeding	% children with MDD
India	33051.4	62072	67.1%	17.9%	53.1%	11.9%	17.9%	41.6%	28.5%	84.9%	23.6%
Nigeria	8956.6	8575	84.1%	35.6%	30.5%	35.9%	16.9%	42.3%	16.6%	73.4%	22.7%
Indonesia	7318.8	4943	94.6%	30.9%	49.3%	57.8%	51.8%	79.3%	27.4%	71.5%	54.3%
Pakistan	7253.8	3141	78.3%	7.7%	57.8%	13.1%	30.9%	18.6%	28.2%	68.6%	15.0%
Bangladesh	4753.1	2321	78.9%	7.5%	38.4%	44.0%	28.7%	40.6%	19.7%	93.9%	26.7%
Ethiopia	4533.2	1460	71.4%	24.9%	35.0%	8.8%	18.2%	26.7%	10.6%	85.2%	13.5%
Congo (Dem. Rep.)	4241.1	2552	65.1%	11.6%	9.1%	49.0%	9.2%	65.6%	25.7%	88.1%	16.2%
Egypt	3921.1	4815	78.1%	23.7%	68.8%	36.4%	30.6%	30.6%	43.4%	64.9%	34.7%
Tanzania	2781.8	3014	90.6%	37.1%	22.9%	32.5%	7.4%	66.0%	20.2%	81.0%	21.5%
Kenya	2189.8	2786	86.4%	26.5%	57.3%	22.6%	18.0%	66.2%	34.4%	83.4%	36.1%
Uganda	2091.3	4128	82.4%	50.9%	29.4%	35.0%	13.7%	51.1%	45.0%	78.2%	31.7%
South Africa	1633.3	861	87.8%	14.1%	75.1%	46.8%	42.0%	51.1%	42.9%	41.3%	39.2%
Angola	1525.8	3872	71.7%	22.0%	26.9%	60.1%	14.3%	57.9%	30.8%	75.9%	28.7%
Mozambique	1446.7	3261	85.6%	28.2%	13.3%	41.7%	17.9%	59.8%	33.3%	82.7%	28.1%
Myanmar	1393.7	1334	70.8%	22.7%	19.5%	44.3%	31.4%	39.0%	15.4%	84.9%	21.1%
Ghana	1248.9	847	88.0%	13.2%	22.5%	53.7%	20.4%	41.1%	22.2%	84.1%	24.2%
Cote d'Ivoire	1179.8	1108	82.8%	4.1%	14.8%	54.9%	9.6%	17.1%	10.8%	76.0%	7.7%
Colombia	1167.7	4962	92.7%	26.3%	84.8%	75.6%	44.6%	52.2%	53.8%	54.9%	61.9%
Yemen	1159.2	4244	84.6%	21.6%	77.1%	27.1%	14.5%	28.3%	12.0%	70.9%	21.5%
Cameroon	1141.3	2549	85.4%	11.5%	21.7%	52.4%	13.7%	49.7%	35.8%	59.3%	18.2%
Niger	1044.6	1559	75.2%	12.9%	17.6%	15.0%	4.9%	27.7%	6.5%	86.1%	8.1%
Madagascar	1028.9	1618	92.3%	19.4%	28.9%	40.9%	4.6%	58.0%	26.4%	85.0%	20.8%
Mali	1012.5	2704	69.5%	11.9%	28.9%	45.4%	14.5%	42.0%	12.8%	84.8%	21.3%
Peru	898.7	2718	95.2%	39.9%	45.8%	75.8%	51.3%	69.4%	78.3%	75.2%	72.2%
Burkina Faso	866.3	2065	64.1%	6.6%	11.8%	20.7%	5.0%	22.9%	5.0%	93.4%	4.9%
Nepal	839.2	1459	92.2%	70.2%	53.4%	25.0%	13.5%	46.7%	37.3%	95.7%	45.0%
Zambia	821.3	2773	86.3%	23.1%	12.4%	43.1%	23.4%	64.2%	27.4%	74.0%	23.6%
Senegal	795.5	1760	81.3%	9.1%	37.7%	43.7%	8.7%	45.0%	8.1%	81.4%	19.5%
Malawi	787.6	4727	69.2%	26.0%	11.8%	32.0%	11.9%	74.3%	28.8%	87.3%	22.8%
Chad	766.3	2914	61.3%	7.7%	25.2%	33.5%	7.7%	24.9%	9.6%	85.6%	9.5%
Zimbabwe	629.4	1599	93.9%	20.3%	20.7%	43.2%	16.0%	59.7%	27.1%	69.0%	22.1%
Guatemala	601.7	3501	93.6%	63.9%	44.1%	41.5%	51.1%	53.9%	48.7%	78.7%	59.3%
Burundi	586.5	3844	71.2%	55.6%	6.7%	22.9%	3.9%	83.4%	7.6%	92.7%	17.6%
Cambodia	562.7	1420	92.0%	8.7%	31.5%	78.1%	38.9%	59.7%	29.8%	69.8%	40.6%
Rwanda	559.1	2292	73.7%	73.1%	30.0%	19.2%	7.8%	82.2%	21.9%	93.0%	34.5%
Benin	545.4	3868	53.9%	25.4%	30.8%	47.5%	22.3%	31.2%	27.2%	79.5%	25.2%
Guinea	506.9	1898	66.4%	3.1%	25.4%	23.7%	19.1%	35.6%	10.1%	82.2%	13.8%
Tajikistan	403.2	1713	82.4%	7.7%	64.0%	22.4%	27.3%	22.2%	31.9%	68.3%	22.4%
Togo	384.3	1054	81.8%	16.6%	11.0%	55.4%	10.7%	53.6%	10.5%	87.1%	19.1%
Haiti	339.7	1647	86.3%	48.3%	32.7%	30.9%	9.1%	39.9%	13.2%	66.0%	19.2%
Honduras	330.0	3225	91.5%	57.3%	75.8%	49.5%	57.8%	39.6%	44.7%	66.2%	60.7%
Sierra Leone	327.0	2632	81.1%	18.7%	33.9%	47.5%	17.6%	45.1%	21.8%	75.6%	25.1%
Dominican Rep.	319.8	1037	88.6%	55.7%	85.3%	53.1%	36.0%	46.2%	39.5%	33.3%	48.5%
Jordan	305.0	2612	78.3%	15.9%	92.0%	37.0%	46.1%	33.5%	45.8%	37.9%	34.7%
Congo	256.4	1489	85.0%	10.0%	47.7%	60.1%	8.3%	47.7%	11.8%	62.2%	17.2%
Kyrgyz Republic	230.4	1310	81.8%	5.8%	61.8%	51.4%	34.2%	30.9%	44.7%	70.1%	37.1%
Liberia	206.2	1507	71.3%	6.8%	14.8%	46.9%	8.0%	40.0%	11.0%	78.4%	8.7%
Mauritania	191.0	3061	60.7%	17.4%	64.9%	32.3%	8.4%	40.3%	14.0%	76.6%	20.2%
Gambia	118.2	2302	88.3%	15.5%	35.4%	47.1%	12.9%	22.6%	22.3%	82.6%	20.1%
Namibia	110.5	648	64.8%	9.4%	34.0%	61.9%	22.2%	37.6%	29.1%	58.0%	23.5%
Gabon	85.4	1176	80.1%	7.0%	71.5%	50.3%	18.2%	39.3%	17.6%	42.1%	18.2%
Lesotho	84.0	466	86.5%	18.9%	34.3%	23.2%	25.4%	37.3%	19.7%	65.8%	14.2%
Armenia	66.4	499	95.4%	4.8%	76.4%	45.8%	20.8%	45.9%	68.6%	43.9%	36.2%
Albania	51.7	759	73.7%	36.2%	80.8%	46.6%	51.8%	55.5%	55.9%	55.7%	52.5%
Timor-Leste	47.3	1935	63.2%	20.1%	24.9%	31.1%	35.7%	61.1%	36.4%	64.0%	27.4%
Comoros	35.8	863	80.9%	9.8%	36.7%	53.3%	21.3%	43.2%	16.4%	73.0%	21.8%
Guyana	22.1	606	81.2%	22.3%	80.9%	62.1%	34.3%	61.1%	34.4%	63.4%	48.5%
Maldives	10.5	847	91.4%	37.3%	90.3%	66.2%	37.1%	75.8%	58.0%	78.3%	71.0%
Sao Tome & Principe	9.2	562	89.4%	11.3%	57.2%	74.9%	22.3%	63.7%	34.9%	68.1%	46.5%
Total (Weighted)*	**109776**	**197514**	**76.9%**	**21.9%**	**43.1%**	**30.2%**	**22.0%**	**45.2%**	**26.5%**	**79.0%**	**26.2%**
Total (Unweighted)**			**80.4%**	**23.2%**	**42.0%**	**42.4%**	**22.4%**	**47.3%**	**28.0%**	**73.5%**	**28.8%**

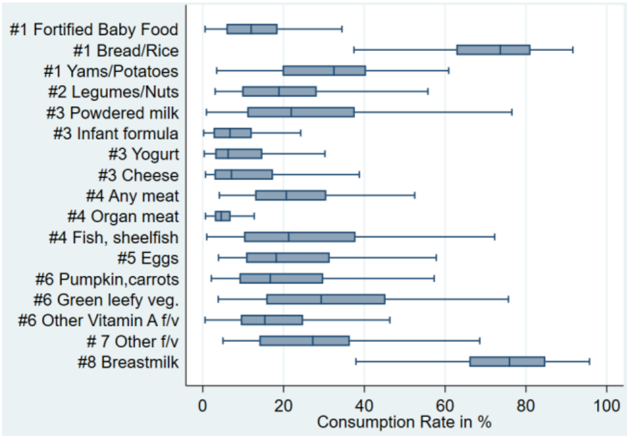
* Weighted by Pop Weights AND Country Size
** Weighted by Pop Weights BUT NOT Country Size

Figure III.2a: Distribution of countries by food- groups



Equal country weights

Figure III.2b: Distribution of countries by food-items



Looking at individual food items that are assigned to the respective food groups, we found that across the whole sample, consumption levels do differ significantly for multiple food items belonging to one food group. For the four food groups that consist of multiple food items (i.e. #1 Grains, #3 Dairy, #4 Flesh Foods, #6 Vitamin A rich Fruits/Veg.), intra-food group consumption levels ranged from 13.7- 69.1% (#1 Grains), 8.9-28.3% (#3 Dairy), 5.9-17.4% (#4 Flesh Foods) and 15.7-33.2% (#6 Vitamin A-rich Fruits/Veg.) (Supplement Table 1). Furthermore, we found that the high consumption levels of food group #1 Grains could be mostly attributed to food item “Bread, rice, noodles” while the variation of intra-country variation of protein-rich food group #3 Dairy and #4 Flesh Foods seemed to be explained much more by the consumption of all food items belonging to that food group (Figure 2b). We also found high inter-country variation of consumption levels for each food item ranging between 75.6 pp. for “Powdered/tinned milk” (76.5 (1.7) % in Guyana and 0.9 (0.2) % in Peru) to 16.2 pp. for “Organ meats”. A granular overview of country-specific food item consumption levels can be found in the Annex (Supplement Table 1).

Variation by socio-economic characteristics

Food consumption patterns depended on several different factors in a child’s household such as a household’s wealth, a child’s age or parental education. We ran fixed effect logit regressions including a set of household covariates (Table 2a and 2b). For most food items, we found strong and significant associations for age, maternal education, and household wealth position. Age appeared to be most relevant when it comes to consuming “Bread/rice/noodles”, the food item belonging to group #3 Flesh Foods and # 8 Breastmilk.

Table III.2a: Regression Results of socio-economic household characteristics on food item consumption levels (food items of groups #1-3)

VARIABLES	Fortified baby food	Bread, rice, noodles	Potatoes, yams, roots	Legumes or nuts	Milk (powder, tinned, fresh)	Infant formula	Yogurt	Cheese/ other milk products
Female Sex	-0.01	0.03	0.01	0.01	-0.04*	-0.06*	0.02	0.05
CI	[-0.06 - 0.04]	[-0.01 - 0.07]	[-0.03 - 0.05]	[-0.03 - 0.05]	[-0.08 - 0.00]	[-0.12 - 0.01]	[-0.04 - 0.08]	[-0.01 - 0.10]
Age of child (base 6-11mths)								
Age Group 12-17mth	**-0.38*****	**1.06*****	**0.61*****	**0.67*****	**0.37*****	**-0.42*****	**0.41*****	**0.57*****
Ci	[-0.44 - -0.32]	[1.02 - 1.10]	[0.57 - 0.66]	[0.62 - 0.72]	[0.32 - 0.43]	[-0.49 - -0.35]	[0.33 - 0.49]	[0.50 - 0.65]
Age Group 18-23mth	**-0.57*****	**1.29*****	**0.78*****	**0.82*****	**0.52*****	**-0.62*****	**0.47*****	**0.76*****
CI	[-0.64 - -0.50]	[1.24 - 1.34]	[0.73 - 0.83]	[0.77 - 0.87]	[0.47 - 0.58]	[-0.70 - -0.54]	[0.38 - 0.55]	[0.69 - 0.84]
Age at birth (mother)	0.00	**-0.01*****	0.00*	0.00*	0.00	**0.01*****	-0.00	-0.00
CI	[-0.00 - 0.01]	[-0.01 - -0.00]	[-0.00 - 0.01]	[-0.00 - 0.01]	[-0.00 - 0.00]	[0.00 - 0.01]	[-0.01 - 0.00]	[-0.01 - 0.00]
Maternal Education (base "No education")								
Primary edu (mother)	**0.26*****	**0.08*****	**0.06****	0.03	0.06*	**0.18*****	**0.20*****	**-0.11****
CI	[0.18 - 0.34]	[0.02 - 0.13]	[0.01 - 0.12]	[-0.03 - 0.09]	[-0.00 - 0.13]	[0.07 - 0.29]	[0.09 - 0.31]	[-0.20 - -0.02]
Secondary edu (mother)	**0.65*****	**0.12*****	**0.18*****	0.04	**0.40*****	**0.61*****	**0.55*****	**0.22*****
CI	[0.56 - 0.74]	[0.06 - 0.19]	[0.12 - 0.25]	[-0.03 - 0.11]	[0.33 - 0.47]	[0.50 - 0.72]	[0.43 - 0.66]	[0.12 - 0.32]
Higher edu (mother)	**0.86*****	**0.17*****	**0.24*****	0.09	**0.43*****	**0.90*****	**0.53*****	**0.25*****
CI	[0.73 - 0.99]	[0.07 - 0.27]	[0.14 - 0.33]	[-0.02 - 0.20]	[0.33 - 0.54]	[0.76 - 1.05]	[0.38 - 0.69]	[0.12 - 0.38]
HH Wealth Decile (base lowest decile)								
HH Decile 2	**0.15*****	**0.09****	0.04	**0.13*****	-0.02	**0.24*****	0.04	0.04
CI	[0.04 - 0.27]	[0.01 - 0.16]	[-0.03 - 0.11]	[0.05 - 0.21]	[-0.11 - 0.07]	[0.08 - 0.39]	[-0.11 - 0.19]	[-0.09 - 0.17]
HH Decile 3	**0.31*****	**0.12*****	**0.10*****	**0.19*****	0.02	**0.43*****	0.07	0.11
CI	[0.20 - 0.43]	[0.05 - 0.20]	[0.03 - 0.18]	[0.11 - 0.28]	[-0.08 - 0.11]	[0.26 - 0.59]	[-0.08 - 0.22]	[-0.03 - 0.24]
HH Decile 4	**0.37*****	**0.15*****	0.07	**0.17*****	0.09*	**0.49*****	**0.18****	**0.19*****
CI	[0.25 - 0.49]	[0.07 - 0.23]	[-0.01 - 0.14]	[0.08 - 0.25]	[-0.01 - 0.19]	[0.33 - 0.65]	[0.02 - 0.33]	[0.07 - 0.32]
HH Decile 5	**0.51*****	**0.19*****	**0.18*****	**0.28*****	0.03	**0.59*****	**0.21*****	**0.26*****
CI	[0.39 - 0.63]	[0.11 - 0.27]	[0.11 - 0.26]	[0.20 - 0.37]	[-0.07 - 0.13]	[0.43 - 0.75]	[0.06 - 0.36]	[0.13 - 0.38]
HH Decile 6	**0.51*****	**0.15*****	**0.13*****	**0.32*****	**0.25*****	**0.71*****	**0.47*****	**0.31*****
CI	[0.38 - 0.63]	[0.06 - 0.23]	[0.05 - 0.21]	[0.23 - 0.41]	[0.15 - 0.34]	[0.55 - 0.88]	[0.32 - 0.62]	[0.18 - 0.44]
HH Decile 7	**0.70*****	**0.18*****	**0.11****	**0.31*****	**0.29*****	**0.92*****	**0.54*****	**0.40*****
CI	[0.57 - 0.82]	[0.10 - 0.27]	[0.02 - 0.20]	[0.22 - 0.41]	[0.19 - 0.39]	[0.76 - 1.07]	[0.38 - 0.69]	[0.27 - 0.54]
HH Decile 8	**0.85*****	**0.20*****	**0.15*****	**0.32*****	**0.43*****	**1.00*****	**0.67*****	**0.44*****
CI	[0.72 - 0.98]	[0.11 - 0.29]	[0.05 - 0.24]	[0.22 - 0.42]	[0.33 - 0.54]	[0.84 - 1.17]	[0.50 - 0.83]	[0.30 - 0.58]
HH Decile 9	**1.00*****	**0.28*****	**0.17*****	**0.41*****	**0.56*****	**1.29*****	**0.92*****	**0.65*****
CI	[0.87 - 1.13]	[0.18 - 0.38]	[0.07 - 0.27]	[0.30 - 0.52]	[0.45 - 0.67]	[1.12 - 1.46]	[0.75 - 1.09]	[0.50 - 0.80]
HH Decile 10	**1.41*****	**0.21*****	**0.25*****	**0.28*****	**0.81*****	**1.89*****	**1.34*****	**0.77*****
CI	[1.28 - 1.55]	[0.10 - 0.32]	[0.14 - 0.36]	[0.16 - 0.40]	[0.69 - 0.93]	[1.72 - 2.06]	[1.16 - 1.52]	[0.61 - 0.92]
Urban	**0.21*****	-0.02	-0.00	-0.05	0.06*	**0.24*****	**0.41*****	0.08*
CI	[0.13 - 0.29]	[-0.08 - 0.04]	[-0.06 - 0.06]	[-0.11 - 0.02]	[-0.01 - 0.12]	[0.15 - 0.34]	[0.32 - 0.51]	[-0.00 - 0.16]
Observations	194,165	196,273	196,276	196,285	196,243	196,236	186,332	196,248
Survey FE	YES	YES	YES	YES	YES	YES	YES	YES

Equal country weights, ∗,∗∗,∗∗∗ Significant differences between 6-11mth and 18-23mth: ∗P < 0.05, ∗∗P < 0.01, ∗∗∗P < 0.001; 95% CI in brackets

Table III.2b: Regression Results socio-economic household characteristics on food item consumption level (food items of groups #4-8)

VARIABLES	Meat (beef, chicken, etc.)	Organ meat (Liver, etc.)	Fresh or dried fish/shellfish	Eggs	Pumpkin, car-rots,sweetpot.	Dark green leafy veg.	Vitam-A fruits (mango, etc.)	Other f/v	Breastfeeding
Female Sex	0.01	-0.01	0.02	0.03	**0.05****	0.03	0.01	-0.00	0.03
CI	[-0.03 - 0.06]	[-0.08 - 0.06]	[-0.03 - 0.06]	[-0.02 - 0.07]	[0.01 - 0.10]	[-0.01 - 0.06]	[-0.04 - 0.06]	[-0.04 - 0.04]	[-0.02 - 0.07]
Age of child (base 6-11mths)									
Age Group 12-17mth	**0.92*****	**0.79*****	**0.79*****	**0.66*****	**0.40*****	**0.77*****	**0.58*****	**0.66*****	**-1.05*****
Ci	[0.86 - 0.98]	[0.70 - 0.89]	[0.74 - 0.85]	[0.60 - 0.71]	[0.35 - 0.46]	[0.72 - 0.81]	[0.53 - 0.64]	[0.61 - 0.71]	[-1.12 - -0.99]
Age Group 18-23mth	**1.23*****	**0.90*****	**1.02*****	**0.85*****	**0.49*****	**0.97*****	**0.74*****	**0.83*****	**-2.49*****
CI	[1.17 - 1.29]	[0.80 - 0.99]	[0.97 - 1.08]	[0.79 - 0.91]	[0.44 - 0.55]	[0.92 - 1.02]	[0.68 - 0.80]	[0.78 - 0.88]	[-2.55 - -2.42]
Age at birth (mother)	**-0.00****	-0.01	0.00	-0.00	**0.00*****	**0.00*****	-0.00	0.00	**0.01*****
CI	[-0.01 - -0.00]	[-0.01 - 0.00]	[-0.00 - 0.00]	[-0.00 - 0.00]	[0.00 - 0.01]	[0.00 - 0.01]	[-0.01 - 0.00]	[-0.00 - 0.00]	[0.01 - 0.02]
Maternal Education (base "No education")									
Primary edu (mother)	**0.07****	0.08	**0.22*****	**0.24*****	0.03	0.06*	**0.11*****	**0.12*****	-0.06*
CI	[0.00 - 0.14]	[-0.03 - 0.19]	[0.16 - 0.28]	[0.16 - 0.31]	[-0.04 - 0.10]	[-0.00 - 0.11]	[0.04 - 0.18]	[0.06 - 0.19]	[-0.13 - 0.01]
Secondary edu (mother)	**0.28*****	**0.27*****	**0.30*****	**0.43*****	**0.26*****	**0.13*****	**0.22*****	**0.31*****	**-0.29*****
CI	[0.21 - 0.36]	[0.15 - 0.39]	[0.23 - 0.37]	[0.36 - 0.51]	[0.18 - 0.34]	[0.07 - 0.20]	[0.14 - 0.30]	[0.24 - 0.38]	[-0.36 - -0.21]
Higher edu (mother)	**0.33*****	**0.28*****	**0.46*****	**0.45*****	**0.45*****	**0.28*****	**0.39*****	**0.53*****	**-0.54*****
CI	[0.22 - 0.44]	[0.11 - 0.44]	[0.34 - 0.58]	[0.34 - 0.56]	[0.34 - 0.56]	[0.18 - 0.39]	[0.26 - 0.51]	[0.43 - 0.63]	[-0.65 - -0.43]
HH Wealth Decile (base lowest decile)									
HH Decile 2	**0.16*****	0.13	0.03	0.09*	0.07	0.04	**0.12****	**0.18*****	**-0.12****
CI	[0.06 - 0.25]	[-0.03 - 0.29]	[-0.06 - 0.12]	[-0.00 - 0.19]	[-0.03 - 0.17]	[-0.04 - 0.12]	[0.02 - 0.21]	[0.10 - 0.26]	[-0.22 - -0.02]
HH Decile 3	**0.23*****	**0.16****	0.02	**0.18*****	**0.13****	0.01	**0.13*****	**0.24*****	**-0.22*****
CI	[0.13 - 0.33]	[0.00 - 0.33]	[-0.07 - 0.11]	[0.09 - 0.28]	[0.03 - 0.23]	[-0.07 - 0.09]	[0.03 - 0.23]	[0.15 - 0.32]	[-0.32 - -0.12]
HH Decile 4	**0.29*****	0.13	0.01	**0.24*****	**0.20*****	-0.01	**0.25*****	**0.32*****	**-0.33*****
CI	[0.18 - 0.39]	[-0.03 - 0.30]	[-0.09 - 0.10]	[0.14 - 0.34]	[0.10 - 0.30]	[-0.09 - 0.07]	[0.15 - 0.35]	[0.23 - 0.40]	[-0.43 - -0.23]
HH Decile 5	**0.33*****	**0.29*****	0.07	**0.23*****	**0.30*****	0.02	**0.32*****	**0.41*****	**-0.28*****
CI	[0.23 - 0.43]	[0.12 - 0.46]	[-0.03 - 0.16]	[0.13 - 0.32]	[0.20 - 0.40]	[-0.07 - 0.10]	[0.22 - 0.43]	[0.32 - 0.49]	[-0.38 - -0.18]
HH Decile 6	**0.38*****	**0.34*****	0.09*	**0.29*****	**0.27*****	-0.07	**0.35*****	**0.41*****	**-0.35*****
CI	[0.27 - 0.49]	[0.15 - 0.52]	[-0.01 - 0.18]	[0.19 - 0.39]	[0.17 - 0.37]	[-0.15 - 0.02]	[0.24 - 0.46]	[0.32 - 0.49]	[-0.45 - -0.24]
HH Decile 7	**0.42*****	**0.40*****	0.08	**0.38*****	**0.30*****	-0.06	**0.35*****	**0.44*****	**-0.48*****
CI	[0.31 - 0.53]	[0.22 - 0.57]	[-0.02 - 0.19]	[0.28 - 0.49]	[0.19 - 0.41]	[-0.15 - 0.03]	[0.24 - 0.45]	[0.35 - 0.53]	[-0.58 - -0.37]
HH Decile 8	**0.55*****	**0.40*****	0.07	**0.49*****	**0.42*****	-0.06	**0.45*****	**0.67*****	**-0.48*****
CI	[0.44 - 0.67]	[0.22 - 0.58]	[-0.04 - 0.18]	[0.38 - 0.59]	[0.31 - 0.53]	[-0.15 - 0.03]	[0.33 - 0.56]	[0.57 - 0.77]	[-0.59 - -0.37]
HH Decile 9	**0.65*****	**0.51*****	0.09	**0.54*****	**0.49*****	-0.03	**0.48*****	**0.71*****	**-0.71*****
CI	[0.53 - 0.77]	[0.32 - 0.69]	[-0.03 - 0.20]	[0.43 - 0.66]	[0.38 - 0.61]	[-0.13 - 0.08]	[0.35 - 0.60]	[0.61 - 0.82]	[-0.83 - -0.59]
HH Decile 10	**0.84*****	**0.58*****	0.01	**0.71*****	**0.71*****	-0.02	**0.62*****	**0.82*****	**-0.91*****
CI	[0.71 - 0.96]	[0.39 - 0.77]	[-0.12 - 0.13]	[0.59 - 0.84]	[0.59 - 0.83]	[-0.13 - 0.10]	[0.49 - 0.75]	[0.71 - 0.93]	[-1.04 - -0.79]
Urban	**0.10*****	0.05	-0.03	**0.15*****	**0.08****	-0.05	-0.07*	**0.09*****	**-0.14*****
CI	[0.04 - 0.17]	[-0.05 - 0.15]	[-0.10 - 0.04]	[0.09 - 0.22]	[0.02 - 0.15]	[-0.11 - 0.01]	[-0.15 - 0.01]	[0.03 - 0.15]	[-0.21 - -0.08]
Observations	196,265	194,162	194,160	196,285	196,264	196,268	196,261	196,285	196,285
Survey FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

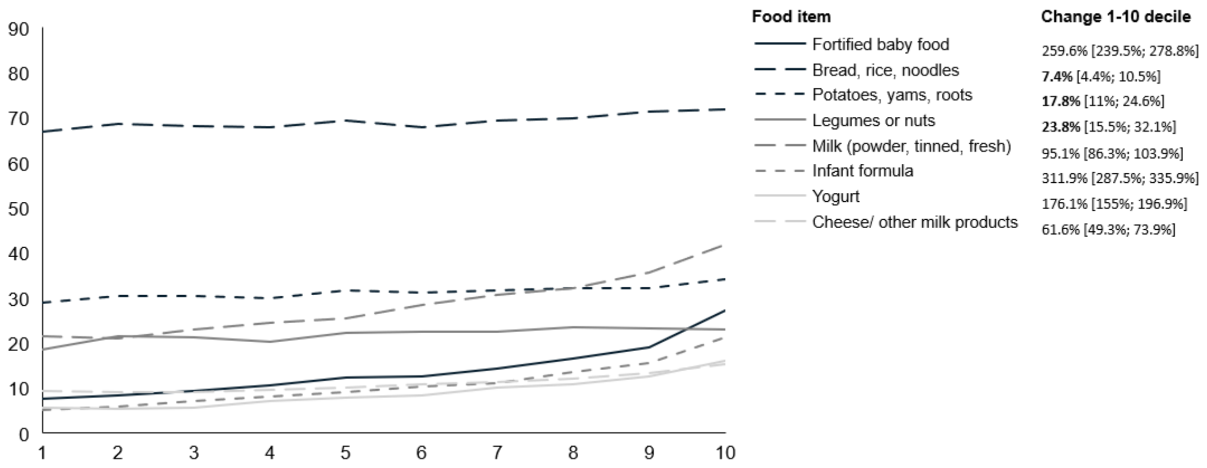
Equal country weights, ∗,∗∗,∗∗∗ Significant differences between 6-11mth and 18-23mth: ∗P < 0.05, ∗∗P < 0.01, ∗∗∗P < 0.001; 95% CI in brackets

A household’s wealth position compared to the lowest decile showed consistently significant associations for most of the food items as well, however becoming statistically relevant at different deciles for different food items. Coefficients for the highest wealth decile were largest for “Fortified baby food”, “Infant formula” and “Yogurt” with a coefficient larger |1|. At the same time for food items “Powdered/tinned milk”, “Yogurt” and “Cheese/other milk products” a significant difference in consumption levels started to appear after passing between the third (“Yogurt”, “Cheese/other milk products”) and the fifth wealth decile (“Powdered/tinned milk”). The consumption of “Fish/shellfish” and “Dark green leafy vegetables” did not seem to be associated with a household’s wealth position. Maternal education showed strongest associations with the consumption of pre-processed baby food, i.e. “Fortified baby food” and “Infant formula”. Finally, urban residency seemed to play a role for #3 Dairy item consumption levels and “Fortified baby food”, but beyond that only showed significance for individual items with small coefficients. Interestingly, sex did not seem to play any role both on a food item level as well as food group level, showing for most items no statistical significance, and for the remaining items very small coefficients. Regression results on a food group level can be found in the Annex (Supplement Table 2).

Variation in Household Wealth

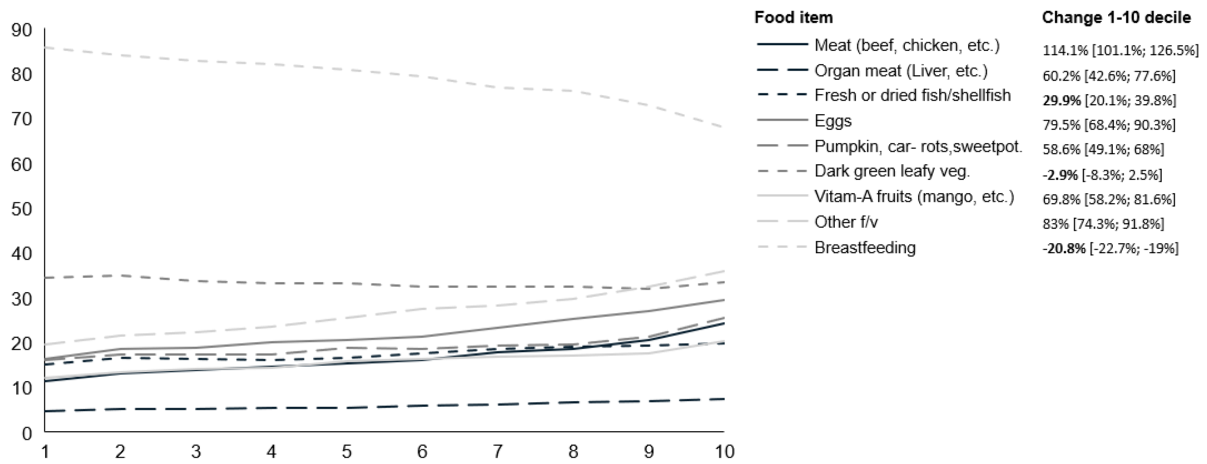
For a household’s wealth position, we found strong and statistically significant regression results for all food items except “Dark green leafy vegetables” and “Fish/shellfish”. These regression results were also reflected when comparing overall consumption levels per wealth decile (Figure 3). Here, the differences between the lowest and highest wealth deciles were particularly high for “Infant formula” (+312%) and “Fortified baby food” (+260%) while levels only changed moderately for “Fish/shellfish” (+30%), “Legumes/nuts” “Bread/rice/noodles” (+7%) and “Dark green leafy vegetables” (-3%). As expected, increasing household wealth was associated with a decline of “Breastfeeding” of -20% between the lowest and the highest wealth decile. On a food group level, we found strong income-related differences for protein-rich food groups #3 Dairy and #5 Eggs as well as #7 Other Fruits/Veg. (Supplement Figure 2). Finally, moving from the lowest to the highest wealth decile was associated with an increase in children meeting MDD levels by 17.9 pp. increase from 19.0 (0.3)% in the lowest wealth decile to 36.9 (0.4)% in the highest wealth decile (Supplement Table 3).

Figure III.3a: Food item consumption levels for different household wealth deciles (food items of groups #1-3)



Changes in percent with 95% CI in brackets; bold numbers with increases <+30%, countries weighted by population size

Figure III.3b: Food item consumption levels for different household wealth deciles (food items of groups #4-8)

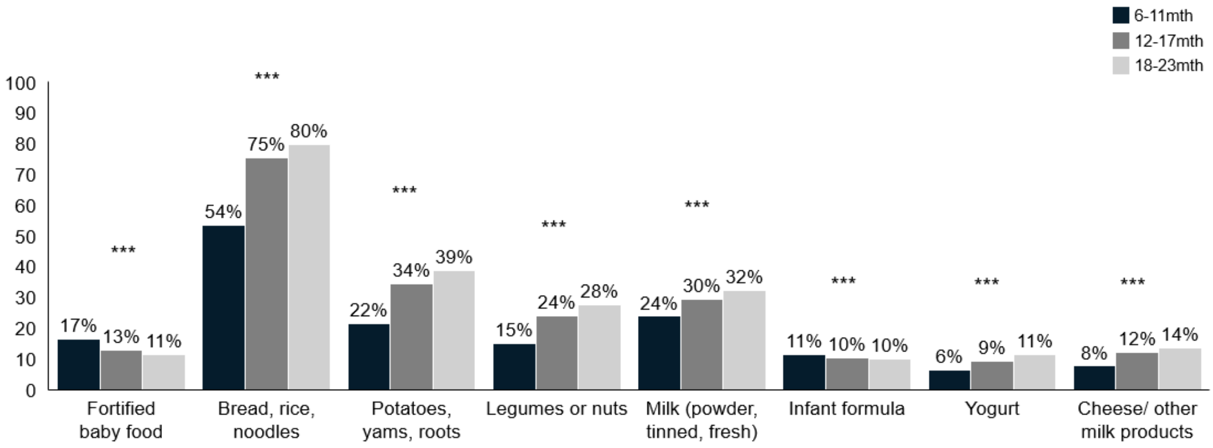


Changes in percent with 95% CI in brackets; bold numbers with increases <+30%, countries weighted by population size

Variation in Child Age

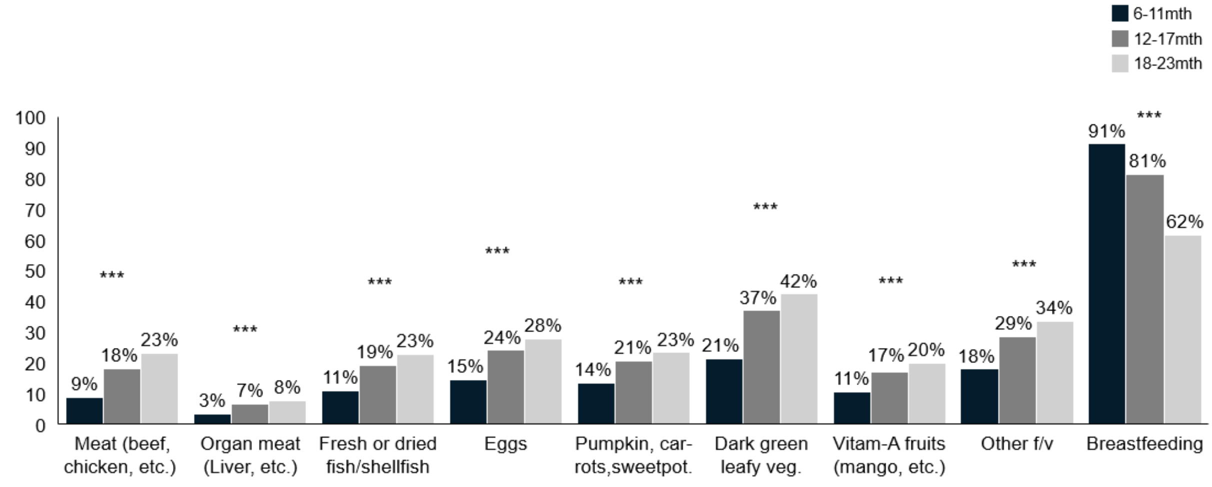
Age seemed to play an important role for consumption levels as well, given that we found positive significant associations between consumption levels and age in months, as well as a negative relationship between the order of birth and consumption levels. Consumption levels increased for all food items increase with age except for "Breastfeeding", which declined by -29.6 pp. between age groups 6-11mth and 18-23mth (Figure 4). The absolute increases with age were particularly pronounced for "Bread/rice/noodles" with +26 pp. and "Dark green leafy vegetables" with +21 pp. For protein rich food groups (Supplement Figure 3) and food items, age variation was lower, however overall consumption levels remain at less than one third for all the respective items across all age groups.

Figure III.4a: Food item consumption levels for separate age groups



Food group consumption for different age groups, countries weighted by population size, ∗,∗∗,∗∗∗ Significant differences between 6-11mth and 18-23mth: ∗P < 0.05, ∗∗P < 0.01, ∗∗∗P < 0.001.

Figure III.4b: Food item consumption levels for separate age groups



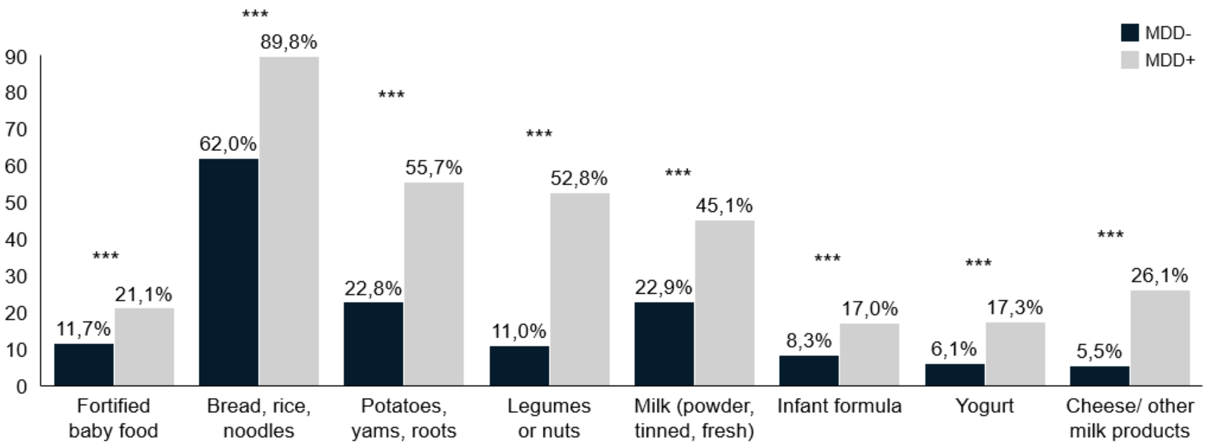
Food group consumption for different age groups, countries weighted by population size, ∗,∗∗,∗∗∗ Significant differences between 6-11mth and 18-23mth: ∗P < 0.05, ∗∗P < 0.01, ∗∗∗P < 0.001.

Finally, the share of children reaching MDD increased with age. 32.3 (0.2)% of children in the oldest age group in our sample (between 18-23mth) achieve MDD, while for children aged 12-17mth it is 29.9 (0.2)% and for the youngest group 6-11mth it is 17.1 (0.1)% (Supplement Table 4).

Variation by MDD status

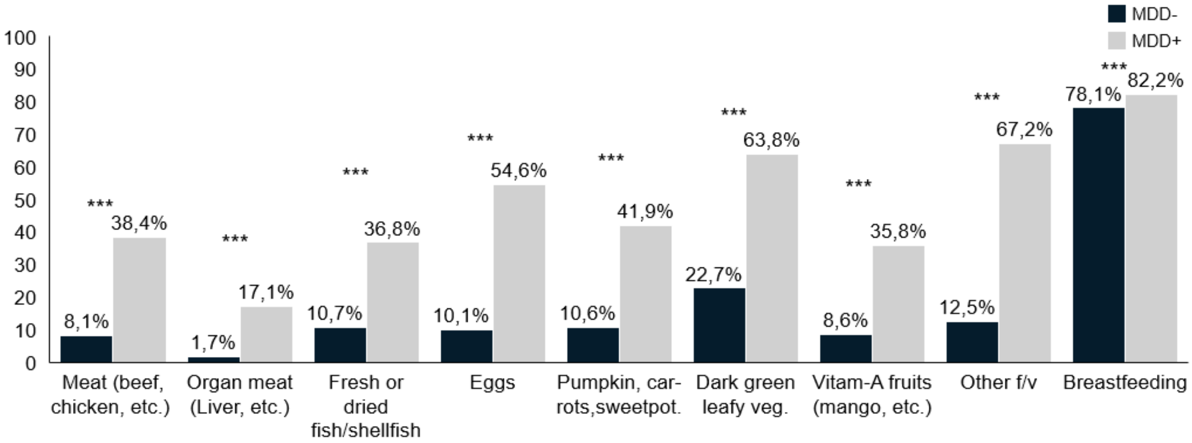
Comparing average food item consumption for children that did meet MDD vs. those that did not, we found consumption levels of "Other Fruits/Veg." as well as "Legumes/nuts", "Eggs" and "Dark green leafy vegetables" differed by more than 40 pp. for children meeting MDD vs. not meeting MDD (Figure 5). Comparing how consumption levels of food groups increased by increasing MDD score, we found that food items #1 Grains quickly increased at low MDD score levels, followed by #6 Vitamin A rich Fruits/Veg. and #4 Dairy (Figure 6) while #8 Breastmilk had high levels of roughly 80% across all MDD scores >=1. Food groups #2 Legumes/nuts, #4 Flesh Foods, #5 Eggs and #7 Other Fruits/Veg. meanwhile showed their largest increases beyond the threshold of having consumed at least 5 different food groups in the past 24 hours.

Figure III.5a: Food item consumption levels by status of reaching minimal dietary diversity for food items belonging to food groups #1-3



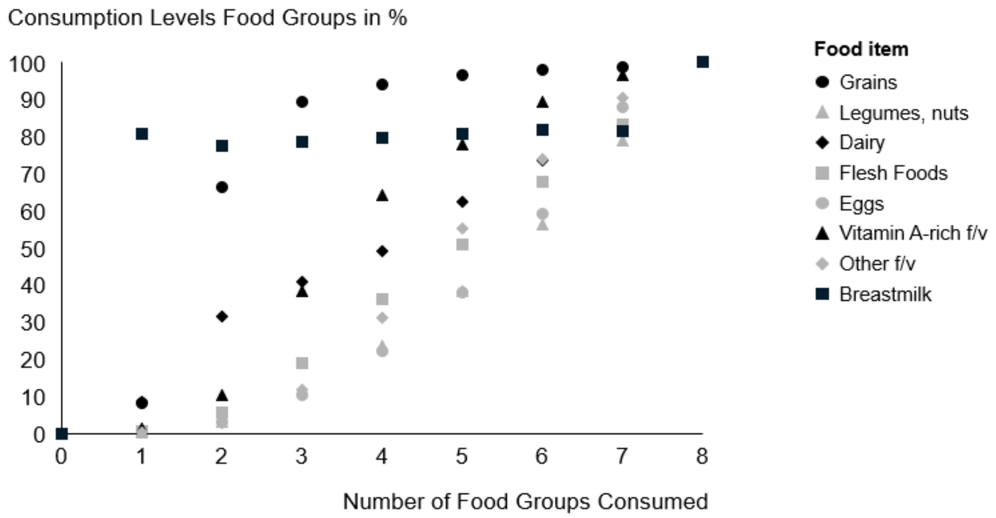
Food group consumption among children 6–23 month old not meeting, weighted by country size, MDD (MDD−, n = 151,310) and meeting MDD (MDD+, n = 50,173) ∗,∗∗,∗∗∗ Significant differences between MDD− and MDD+: ∗P < 0.05, ∗∗P < 0.01, ∗∗∗P < 0.001. "Grains" includes grains, roots, and tuber

Figure III.5b: Food item consumption levels by status of reaching minimal dietary diversity for food items belonging to food groups #4-8



Food group consumption among children 6–23 month old not meeting, weighted by country size, MDD (MDD−, n = 151,310) and meeting MDD (MDD+, n = 50,173) ∗,∗∗,∗∗∗ Significant differences between MDD− and MDD+: ∗P < 0.05, ∗∗P < 0.01, ∗∗∗P < 0.001.

Figure III.6: Food group consumption levels by number of food groups consumed



III.4. Discussion

Our study has several salient findings. At first, food group consumption levels across 59 LMICs are particularly low for protein rich food groups such as #2 Legumes/nuts, #4 Flesh foods and #5 Eggs, as well as #7 Other non-vitamin-A rich Fruits/Veg. These consumption patterns are in line with existing literature pointing towards global protein energy malnutrition particularly in LMICs.[14,15] Second, given the high observed intra-food group variation of consumed food items, it is necessary to look at food item specific consumption levels to better understand the observed patterns and address them with targeted and effective policies, which is in line with literature emphasizing the need to increasingly focus on child's diet itself.[6,22]

Third, food group and item consumption are influenced by multiple factors related to the child itself as well as the household it lives in. Among the most influential correlates the household's wealth and a child's age were identified. However, significance and magnitude differed depending on the individual food item. Household wealth (measured by its wealth decile) was most relevant for pre-processed foods such as "Infant formula" and "Fortified baby food". For "Powdered/tinned milk" or "Cheese" and "Yogurt" a household's wealth only became statistically significant once the 5th and 3rd wealth decile were passed while it did not show statistical significance for food items "Fish/shellfish" and "Dark green leafy vegetables". This points to the relevance of household resources particularly for processed and protein rich food items, that one would need to purchase, that may rely on cooling infrastructure and that would come at a higher price as opposed to agricultural/plant-based produce. For items which showed little association (in terms statistical associations and total increases) of consumption levels and wealth, this could be explained by either low prices or general availability in nature for the specific items (e.g. "Potatoes, yams" or "Dark green leafy vegetables") or on the other hand limited availability or cultural reasons in case of low consumption levels overall (e.g. "Legumes/nuts" or "Fish/shellfish). Urban residency also seems to play a role when it comes to the availability of preprocessed food ("Infant formula" and "Fortified baby food") as well as other dairy categories that rely on a certain supply chain while it is negatively associated with "Breastfeeding" that may hint towards more alternatives in children's diet in urban dwellings. Overall, most food group consumption seems to be strongly associated with wealth (i.e. #3 Dairy, #4 Flesh Foods, #5 Eggs and #7 Other non-vitamin-A rich Fruits/Veg.), while #2 Legumes/Nuts and #6 Vitamin A-rich fruits/veg. consumption seem to be more related to its availability in a country rather than wealth. The older children become, the higher consumption rates become for the different food items except for "Breastmilk", where we found large decreases in consumption with age. These patterns could be explained both by limited household resources as well as educational gaps, e.g. lack of awareness that children already have dietary diversity needs as early as 6 months of age even while being breastfed or that children may still rely on breastmilk up to the age of 23 months.

Finally, across 59 LMICs, roughly 73.8% of children aged 6-23 months did not meet WHO's minimal dietary diversity requirement, underscoring the magnitude of child malnutrition across the globe which is also in line with studies documenting large shares of children not reaching minimum dietary diversity in national settings.[15-18] As stated above, there are various potential reasons explaining the observed food item consumption patterns, such as local (national and regional) availability or socio-economic factors such as lack of awareness/education, cultural predispositions, religion, or limited resources.[19-21] For policymakers to effectively craft targeted interventions, it is important to understand which mechanisms are at play in which setting.

Policy Implications

Our results shows that food group and more specifically food item consumption data adds important insights for policymakers beyond the binary outcome MDD. To properly identify needs and target groups, it is important to attain total consumption levels for food groups as well as food items for various subpopulations. Possible food items/groups for interventions can be those with overall low consumption levels, however it may also make sense to focus on those groups, separating children with MDD from those without, i.e. those food groups, that show strong increases in consumption levels between MDD score of 4 and 5. Across all LMICs, #7 Other Fruits/Veg. and #5 Eggs would be such food groups. Considering the intra-food group variation of consumption levels of individual food items, it is important for policymakers to look at food item consumption levels for those food groups (e.g. protein rich groups) identified as particularly relevant and identify the drivers of consumption, i.e. whether there is a single food item explaining consumption levels (e.g. food item "Bread/rice/noodles" with 70.1% consumption as part of food group #1 Grains with 76.9% consumption across sample) or whether the food group consumption levels are explained more evenly by food items (see items "Any meat" with 16.4% and "Fish/shellfish" with 17.4% consumption as part of food group #4 Flesh Foods with overall 30.2% consumption levels). In case of the former, reinforcing measures such as supplementation or food vouchers for the most relevant individual food items or micronutrients[22,23] may prove most successful and cost efficient while for the latter, measures may want to address food item consumption more broadly.[24,25]

To properly promote food item consumption, it is important to understand the potentially multiple drivers of observed consumption levels, which can be categorized in availability (regional/local availability), education/culture as well as household resources. For those items that either show low levels of consumption for all sub-populations that would not be explained by cultural/religious reasons (e.g. #2 Legumes/nuts) or items that show large urban/rural consumption differences, programs promoting availability, storage stability and support of local supply chains (e.g. cooling capacities) may ensure higher dietary diversity on a national level as well as in remote areas.[26] For items that show strong association with household wealth in terms of significance and coefficient, targeted food vouchers or cash transfers may be a viable policy option supporting not only household resources but also serving as a signaling effect towards a food item's relevance.[24,25,27] Finally, for items that increase/decrease particularly strong with age or that are associated with parental education, educational campaigns about early childhood needs may prove effective.[28,29] This could be complemented by supporting households with multiple children with targeted food support programs for the youngest children to both promote dietary diversity for the youngest and prevent resource pooling in older siblings.

Overall, given the observed inter-country variation in consumption patterns, looking at countries with high levels of specific food item consumption may point policymakers towards potential policy or intervention best practices. The high inter-country variation furthermore points to the needs of policymakers to attain local representative and up-to-date food item consumption data to identify needs, prioritize and derive effective and targeted measures.

Limitations

Our analysis has three sources of data limitations. First, there may be a certain degree of measurement error for MDD and individual food group consumption. Given that the dietary data were self-reported by mothers based on a 24h recall, data may be subject to measurement error due missing memory or overreporting due to social desirability. However, given our large sample, we do not believe that recall errors produce any bias in our results and furthermore, DHS data on dietary intake has been found to be appropriate at the population level.[30] The India and Mauritania data comes from the most recent 2019-2021 survey, that also contains interviews that were conducted in 2021. We are aware that during this time, feeding practices may have changed due to thy dynamics of the COVID-19 pandemic. However, we decided to accept a certain degree of COVID-19 bias for these two countries with the benefit of getting most recent data (in case of Mauritania any data at all), especially as most of the interviews were conducted prior to the COVID-19 pandemic really starting to hit these countries. Our estimates may also be biased by survey non-response and missing data for specific survey items or countries. However, we expect such bias to be small, given that we attained complete nutrition data for an average of ~97 percent of all children in the sample for 59 out of the 61 countries that conducted the standard DHS surveys in the past 12 years (missing countries:

Afghanistan and the Philippines). Overall, the countries in our sample account for 63.1 percent of worldwide LMICs child population (0-5 years old). The results are driven to a certain extent by very large countries in our sample, such as India, which accounts for roughly one third of the entire sample population. Even though assigning equal weights to countries changes our results to a certain degree (e.g. 28.8 percent of children reaching MDD with equal weights vs. 26.2 percent of children reaching MDD with country population weights), the overall message remains the same, i.e. that there are is a large degree of unmet nutritional needs among children aged 6-23months in LMICs and that it is important to look beyond the binary indicator of MDD, given that for different countries and local sub-populations varying food groups and items show large variation. Finally, the binary data for the individual food group consumption does not provide any information on quantities consumed or frequency of consumption within the past 24 hours. We would have also liked to control for local prices as part of our analyses, however were not able to find locally PPP adjusted prices on food item level for the countries in the years of the respective DHS surveys. Both food item quantities as well as local and regional prices are subject to future research and data collection. The availability of more ample and granular data will open a whole new set of research opportunities to the field. Unfortunately, to the best of our knowledge, no such dataset exists for a large cross-country sample yet.

III.5. Conclusion

The analysis of dietary diversity should be complemented with analyses of individual food item consumption, given that consumption patterns vary significantly for different countries and sub-groups. Studying these food group and more specifically food item consumption patterns at first help policymakers to identify specific micronutrient related needs as well as help to better understand underlying reasons for observed consumption patterns and as such inform about potential channels to successfully address these needs and as such fight child undernutrition across the globe.

III.6 Appendix

Supplement Table III.1: Food item consumption levels for seventeen food items that can be allocated into WHO's MDD food groups

	#1 Grains				#2 Legu-mes	#3 Dairy					#4 Flesh foods				#5 Eggs	#6 Vitamin-A-rich fruits/vegetables				#7 Other f/v	#8 Breast-feed.
Country	**Fortified baby food**	**Bread, rice, noodles**	**Potatoes, yams, roots**	*At least one*	*Total*	**Milk (powder, tinned, fresh)**	**Infant formula**	**Yogurt**	**Cheese / other milk products**	*At least one*	**Meat (beef, chicken, etc.)**	**Organ meat (Liver, etc.)**	**Fresh or dried fish/shellfish**	*At least one*	*Total*	**Pumpkin, car-rots,s weetpot.**	**Dark green leafy veg.**	**Vitam-A fruits (mango, etc.)**	*At least one*	*Total*	*Total*
Albania	8.7%	68.5%	37.1%	73.7%	36.2%	41.8%	12.0%	46.0%	53.0%	80.8%	41.3%	11.7%	10.8%	46.6%	51.8%	44.5%	30.9%	25.7%	55.5%	55.9%	55.7%
Angola	12.1%	61.0%	33.2%	71.7%	22.0%	11.0%	6.7%	16.2%	9.5%	26.9%	22.6%	9.1%	54.3%	60.1%	14.3%	21.0%	46.6%	23.0%	57.9%	30.8%	75.9%
Armenia	9.5%	87.3%	75.8%	95.4%	4.8%	34.3%	5.0%	46.1%	32.9%	76.4%	45.0%	1.9%	1.8%	45.8%	20.8%	40.0%	11.2%	7.3%	45.9%	68.6%	43.9%
Bangladesh	6.5%	74.7%	40.6%	78.9%	7.5%	29.8%	6.9%	5.8%	1.1%	38.4%	12.8%	5.9%	35.9%	44.0%	28.7%	6.9%	27.4%	16.0%	40.6%	19.7%	93.9%
Benin	7.1%	34.8%	31.9%	53.9%	25.4%	13.6%	5.0%	8.4%	17.4%	30.8%	20.7%	7.8%	40.4%	47.5%	22.3%	9.3%	23.0%	13.6%	31.2%	27.2%	79.5%
Burkina Faso	4.7%	61.2%	3.5%	64.1%	6.6%	9.4%	2.0%	2.0%	0.7%	11.8%	6.4%	0.7%	16.5%	20.7%	5.0%	2.1%	20.0%	3.3%	22.9%	5.0%	93.4%
Burundi	8.3%	51.8%	38.2%	71.2%	55.6%	5.4%	0.2%	0.6%	0.9%	6.7%	7.8%	3.1%	16.3%	22.9%	3.9%	17.6%	75.7%	40.2%	83.4%	7.6%	92.7%
Cambodia	4.7%	91.0%	13.3%	92.0%	8.7%	21.1%	12.5%	1.7%	1.9%	31.5%	52.5%	12.8%	58.8%	78.1%	38.9%	25.6%	50.7%	12.6%	59.7%	29.8%	69.8%
Cameroon	7.6%	77.3%	16.8%	85.4%	11.5%	10.8%	11.2%	5.4%	2.9%	21.7%	21.0%	2.7%	37.3%	52.4%	13.7%	11.1%	37.1%	16.0%	49.7%	35.8%	59.3%
Chad	23.5%	46.9%	8.1%	61.3%	7.7%	21.9%	3.6%	2.0%	3.3%	25.2%	17.5%	6.2%	21.6%	33.5%	7.7%	5.4%	16.9%	10.0%	24.9%	9.6%	85.6%
Colombia	24.0%	88.7%	60.9%	92.7%	26.3%	45.5%	42.6%	*N/A*	41.4%	84.8%	70.7%	14.9%	10.2%	75.6%	44.6%	35.7%	8.7%	26.2%	52.2%	53.8%	54.9%
Comoros	13.6%	73.2%	28.0%	80.9%	9.8%	17.4%	16.6%	14.4%	6.3%	36.7%	24.2%	6.5%	39.6%	53.3%	21.3%	20.9%	18.0%	26.7%	43.2%	16.4%	73.0%
Congo	14.7%	65.6%	40.0%	85.0%	10.0%	35.8%	12.1%	16.0%	6.2%	47.7%	20.9%	4.4%	39.9%	60.1%	8.3%	9.3%	31.6%	21.4%	47.7%	11.8%	62.2%
Congo (Dem. Rep.)	3.9%	49.0%	30.0%	65.1%	11.6%	6.1%	2.5%	1.1%	1.0%	9.1%	16.4%	3.9%	37.8%	49.0%	9.2%	7.3%	59.2%	16.3%	65.6%	25.7%	88.1%
Cote d'Ivoire	10.4%	70.2%	39.3%	82.8%	4.1%	7.4%	4.3%	8.6%	0.9%	14.8%	15.2%	1.0%	49.3%	54.9%	9.6%	4.6%	7.8%	9.3%	17.1%	10.8%	76.0%
Dominican Rep.	23.4%	79.4%	53.1%	88.6%	55.7%	75.9%	9.5%	7.3%	15.9%	85.3%	47.3%	5.7%	6.2%	53.1%	36.0%	25.8%	4.2%	29.3%	46.2%	39.5%	33.3%
Egypt	5.7%	68.0%	50.3%	78.1%	23.7%	23.9%	4.6%	37.4%	36.1%	68.8%	23.3%	9.5%	7.6%	36.4%	30.6%	6.9%	21.3%	9.6%	30.6%	43.4%	64.9%
Ethiopia	5.3%	63.5%	26.0%	71.4%	24.9%	20.9%	3.7%	4.4%	17.1%	35.0%	5.2%	3.1%	1.9%	8.8%	18.2%	11.4%	12.2%	11.9%	26.7%	10.6%	85.2%
Gabon	34.5%	51.4%	32.4%	80.1%	7.0%	38.5%	35.7%	34.6%	14.7%	71.5%	28.9%	5.3%	25.7%	50.3%	18.2%	16.7%	23.1%	12.3%	39.3%	17.6%	42.1%
Gambia	28.8%	75.7%	13.1%	88.3%	15.5%	27.3%	2.7%	7.9%	2.6%	35.4%	9.0%	1.0%	40.7%	47.1%	12.9%	12.1%	12.0%	1.5%	22.6%	22.3%	82.6%
Ghana	15.8%	82.5%	30.8%	88.0%	13.2%	16.0%	4.0%	3.5%	1.7%	22.5%	13.6%	2.8%	46.5%	53.7%	20.4%	6.9%	36.8%	5.9%	41.1%	22.2%	84.1%
Guatemala	46.9%	89.9%	38.1%	93.6%	63.9%	19.1%	7.9%	10.1%	23.1%	44.1%	36.7%	4.5%	4.3%	41.5%	51.1%	30.0%	20.3%	23.7%	53.9%	48.7%	78.7%
Guinea	17.8%	58.2%	9.7%	66.4%	3.1%	14.9%	10.1%	8.9%	5.5%	25.4%	10.2%	3.6%	19.2%	23.7%	19.1%	8.5%	9.7%	31.0%	35.6%	10.1%	82.2%
Guyana	28.7%	65.3%	40.4%	81.2%	22.3%	76.5%	39.1%	*N/A*	33.2%	80.9%	42.7%	12.7%	31.0%	62.1%	34.3%	36.8%	33.5%	32.9%	61.1%	34.4%	63.4%
Haiti	4.4%	81.1%	17.4%	86.3%	48.3%	14.4%	15.4%	0.9%	6.9%	32.7%	21.4%	1.2%	11.1%	30.9%	9.1%	24.4%	23.8%	7.7%	39.9%	13.2%	66.0%
Honduras	29.2%	83.1%	42.9%	91.5%	57.3%	51.0%	4.4%	4.0%	52.9%	75.8%	44.2%	2.6%	7.7%	49.5%	57.8%	26.2%	5.6%	18.1%	39.6%	44.7%	66.2%
India	16.1%	60.2%	26.9%	67.1%	17.9%	42.0%	12.1%	9.9%	12.4%	53.1%	7.7%	6.1%	5.9%	11.9%	17.9%	23.1%	32.0%	15.5%	41.6%	28.5%	84.9%
Indonesia	28.6%	85.3%	33.5%	94.6%	30.9%	12.2%	37.0%	3.0%	7.7%	49.3%	35.3%	15.7%	34.4%	57.8%	51.8%	48.9%	59.5%	43.4%	79.3%	27.4%	71.5%
Jordan	20.7%	64.0%	34.0%	78.3%	15.9%	42.8%	47.3%	60.8%	39.3%	92.0%	30.6%	10.1%	6.8%	37.0%	46.1%	20.6%	16.5%	13.2%	33.5%	45.8%	37.9%
Kenya	5.3%	81.3%	38.7%	86.4%	26.5%	49.9%	5.5%	5.3%	9.5%	57.3%	12.6%	4.0%	10.7%	22.6%	18.0%	28.4%	51.3%	24.8%	66.2%	34.4%	83.4%
Kyrgyz Republic	14.2%	74.5%	60.4%	81.8%	5.8%	27.7%	8.7%	32.3%	25.3%	61.8%	48.8%	12.7%	5.1%	51.4%	34.2%	20.1%	9.0%	17.3%	30.9%	44.7%	70.1%
Lesotho	8.7%	83.4%	15.3%	86.5%	18.9%	22.3%	12.9%	6.4%	2.4%	34.3%	15.8%	6.8%	5.2%	23.2%	25.4%	9.0%	34.1%	1.0%	37.3%	19.7%	65.8%

Liberia	5.9%	62.8%	23.7%	71.3%	6.8%	9.3%	6.4%	1.0%	4.6%	14.8%	18.0%	4.8%	37.8%	46.9%	8.0%	10.4%	35.0%	6.5%	40.0%	11.0%	78.4%
Madagascar	1.9%	88.6%	39.0%	92.3%	19.4%	22.2%	8.0%	*N/A*	5.5%	28.9%	18.5%	3.6%	24.3%	40.9%	4.6%	16.1%	45.3%	14.9%	58.0%	26.4%	85.0%
Malawi	7.8%	61.1%	13.4%	69.2%	26.0%	5.4%	2.6%	4.6%	1.7%	11.8%	13.0%	3.0%	20.9%	32.0%	11.9%	3.8%	61.8%	46.3%	74.3%	28.8%	87.3%
Maldives	42.4%	78.4%	32.5%	91.4%	37.3%	48.8%	43.9%	52.1%	29.0%	90.3%	28.3%	6.2%	50.5%	66.2%	37.1%	62.6%	42.0%	40.6%	75.8%	58.0%	78.3%
Mali	14.8%	64.9%	10.2%	69.5%	11.9%	22.0%	6.2%	6.6%	4.2%	28.9%	24.8%	4.8%	33.3%	45.4%	14.5%	14.7%	34.5%	5.5%	42.0%	12.8%	84.8%
Mauritania	4.7%	54.5%	19.8%	60.7%	17.4%	49.3%	10.1%	25.6%	7.1%	64.9%	21.9%	7.5%	14.7%	32.3%	8.4%	36.9%	9.0%	3.8%	40.3%	14.0%	76.6%
Mozambique	30.3%	74.0%	39.7%	85.6%	28.2%	4.2%	1.5%	3.1%	7.6%	13.3%	19.4%	5.2%	33.1%	41.7%	17.9%	31.0%	49.2%	17.7%	59.8%	33.3%	82.7%
Myanmar	5.0%	66.6%	13.3%	70.8%	22.7%	12.2%	5.0%	0.4%	4.1%	19.5%	26.7%	3.4%	25.1%	44.3%	31.4%	15.2%	29.3%	6.6%	39.0%	15.4%	84.9%
Namibia	15.4%	57.6%	24.1%	64.8%	9.4%	16.3%	10.6%	14.7%	17.2%	34.0%	47.0%	15.4%	26.3%	61.9%	22.2%	19.4%	20.6%	11.2%	37.6%	29.1%	58.0%
Nepal	7.7%	89.4%	58.1%	92.2%	70.2%	48.3%	2.5%	7.6%	8.6%	53.4%	20.8%	6.9%	3.9%	25.0%	13.5%	10.2%	33.7%	13.4%	46.7%	37.3%	95.7%
Niger	4.2%	73.1%	14.4%	75.2%	12.9%	10.6%	1.6%	3.7%	5.4%	17.6%	11.4%	4.5%	3.8%	15.0%	4.9%	5.9%	15.7%	13.8%	27.7%	6.5%	86.1%
Nigeria	4.5%	80.7%	27.6%	84.1%	35.6%	14.9%	6.5%	6.1%	12.2%	30.5%	17.4%	3.9%	24.5%	35.9%	16.9%	9.1%	37.5%	4.1%	42.3%	16.6%	73.4%
Pakistan	18.5%	68.8%	37.0%	78.3%	7.7%	49.0%	6.6%	5.6%	4.4%	57.8%	9.9%	1.8%	2.5%	13.1%	30.9%	8.7%	11.0%	0.6%	18.6%	28.2%	68.6%
Peru	*N/A*	87.6%	77.6%	95.2%	39.9%	0.9%	11.4%	*N/A*	38.8%	45.8%	75.8%	*N/A*	*N/A*	75.8%	51.3%	57.3%	26.4%	17.8%	69.4%	78.3%	75.2%
Rwanda	18.4%	37.4%	47.0%	73.7%	73.1%	27.9%	1.3%	2.1%	0.7%	30.0%	4.1%	1.3%	15.6%	19.2%	7.8%	29.8%	68.0%	43.5%	82.2%	21.9%	93.0%
Sao Tome & Principe	12.2%	80.8%	55.4%	89.4%	11.3%	27.8%	37.8%	*N/A*	19.2%	57.2%	7.1%	2.1%	72.3%	74.9%	22.3%	36.6%	30.9%	35.7%	63.7%	34.9%	68.1%
Senegal	12.4%	76.0%	24.4%	81.3%	9.1%	28.0%	2.6%	6.5%	7.0%	37.7%	6.2%	1.5%	40.7%	43.7%	8.7%	36.9%	15.6%	11.4%	45.0%	8.1%	81.4%
Sierra Leone	24.6%	68.3%	24.6%	81.1%	18.7%	20.1%	20.3%	3.7%	12.4%	33.9%	6.9%	3.6%	45.9%	47.5%	17.6%	14.7%	27.0%	27.3%	45.1%	21.8%	75.6%
South Africa	46.6%	72.0%	42.0%	87.8%	14.1%	30.8%	40.2%	44.0%	21.1%	75.1%	39.9%	14.3%	11.0%	46.8%	42.0%	43.4%	22.5%	9.4%	51.1%	42.9%	41.3%
Tajikistan	6.7%	74.5%	57.0%	82.4%	7.7%	40.4%	11.7%	30.2%	10.8%	64.0%	21.0%	1.7%	1.0%	22.4%	27.3%	17.6%	3.8%	4.0%	22.2%	31.9%	68.3%
Tanzania	11.8%	83.7%	27.0%	90.6%	37.1%	17.7%	1.1%	4.8%	3.5%	22.9%	13.5%	2.5%	21.0%	32.5%	7.4%	11.0%	54.7%	26.8%	66.0%	20.2%	81.0%
Timor-Leste	10.8%	49.2%	32.4%	63.2%	20.1%	11.0%	11.7%	2.5%	8.8%	24.9%	18.9%	16.8%	16.5%	31.1%	35.7%	34.7%	50.1%	22.8%	61.1%	36.4%	64.0%
Togo	4.2%	77.8%	32.5%	81.8%	16.6%	4.9%	2.0%	1.3%	4.8%	11.0%	15.3%	3.0%	47.9%	55.4%	10.7%	5.7%	45.2%	18.8%	53.6%	10.5%	87.1%
Uganda	0.6%	73.7%	36.4%	82.4%	50.9%	27.8%	0.4%	1.8%	2.4%	29.4%	15.0%	3.0%	25.2%	35.0%	13.7%	18.3%	37.5%	15.4%	51.1%	45.0%	78.2%
Yemen	12.4%	76.0%	44.0%	84.6%	21.6%	37.6%	24.2%	19.0%	40.8%	77.1%	14.9%	4.6%	10.7%	27.1%	14.5%	13.8%	6.5%	16.2%	28.3%	12.0%	70.9%
Zambia	16.4%	79.7%	11.2%	86.3%	23.1%	5.3%	1.7%	6.2%	1.7%	12.4%	21.1%	5.3%	23.2%	43.1%	23.4%	8.9%	58.7%	13.4%	64.2%	27.4%	74.0%
Zimbabwe	10.8%	91.6%	15.7%	93.9%	20.3%	6.3%	1.6%	14.8%	2.8%	20.7%	32.2%	6.2%	17.1%	43.2%	16.0%	10.4%	53.0%	13.1%	59.7%	27.1%	69.0%
Total (Weighted)*	13.7%	69.1%	31.3%	76.9%	21.9%	28.3%	10.7%	8.9%	11.0%	43.1%	16.4%	5.9%	17.4%	30.2%	22.0%	19.0%	33.2%	15.7%	45.2%	26.5%	79.0%
Total (Unweighted)**	14.6%	71.1%	32.9%	80.4%	23.2%	25.2%	11.6%	12.6%	13.1%	42.0%	23.7%	5.8%	24.0%	42.4%	22.4%	20.3%	30.4%	17.4%	47.3%	28.0%	73.5%

* Weighted by Pop Weights AND Country Size
** Weighted by Pop Weights BUT NOT Country Size

Supplement Table III.2: Regression Results socio-economic household characteristics on food group consumption level

VARIABLES	Grains	Legumes, nuts	Dairy	Flesh foods	Eggs	Vitamin-A-rich f/v	Other f/v	Breastfeeding
Female Sex	0.02	0.01	-0.02	0.01	0.03	0.03*	-0.00	0.03
CI	[-0.03 - 0.06]	[-0.03 - 0.05]	[-0.06 - 0.02]	[-0.02 - 0.05]	[-0.02 - 0.07]	[-0.00 - 0.07]	[-0.04 - 0.04]	[-0.02 - 0.07]
Age of child (base 6-11mths)								
Age Group 12-17mth	**0.98*****	**0.67*****	**0.31*****	**1.00*****	**0.66*****	**0.76*****	**0.66*****	**-1.05*****
Ci	[0.93 - 1.03]	[0.62 - 0.72]	[0.27 - 0.36]	[0.96 - 1.05]	[0.60 - 0.71]	[0.72 - 0.80]	[0.61 - 0.71]	[-1.12 - -0.99]
Age Group 18-23mth	**1.24*****	**0.82*****	**0.42*****	**1.32*****	**0.85*****	**0.95*****	**0.83*****	**-2.49*****
CI	[1.19 - 1.30]	[0.77 - 0.87]	[0.37 - 0.47]	[1.27 - 1.37]	[0.79 - 0.91]	[0.91 - 1.00]	[0.78 - 0.88]	[-2.55 - -2.42]
Age at birth (mother)	-0.00*	0.00*	0.00	-0.00	-0.00	**0.00****	0.00	**0.01*****
CI	[-0.01 - 0.00]	[-0.00 - 0.01]	[-0.00 - 0.00]	[-0.00 - 0.00]	[-0.00 - 0.00]	[0.00 - 0.01]	[-0.00 - 0.00]	[0.01 - 0.02]
Maternal Education (base "No education")								
Primary edu (mother)	**0.16*****	0.03	-0.01	**0.18*****	**0.24*****	**0.09*****	**0.12*****	-0.06*
CI	[0.11 - 0.22]	[-0.03 - 0.09]	[-0.07 - 0.05]	[0.12 - 0.23]	[0.16 - 0.31]	[0.04 - 0.14]	[0.06 - 0.19]	[-0.13 - 0.01]
Secondary edu (mother)	**0.25*****	0.04	**0.41*****	**0.36*****	**0.43*****	**0.22*****	**0.31*****	**-0.29*****
CI	[0.19 - 0.32]	[-0.03 - 0.11]	[0.35 - 0.48]	[0.30 - 0.42]	[0.36 - 0.51]	[0.17 - 0.28]	[0.24 - 0.38]	[-0.36 - -0.21]
Higher edu (mother)	**0.40*****	0.09	**0.64*****	**0.48*****	**0.45*****	**0.43*****	**0.53*****	**-0.54*****
CI	[0.28 - 0.51]	[-0.02 - 0.20]	[0.54 - 0.75]	[0.39 - 0.58]	[0.34 - 0.56]	[0.33 - 0.52]	[0.43 - 0.63]	[-0.65 - -0.43]
HH Wealth Decile (base lowest decile)								
HH Decile 2	0.06	**0.13*****	0.02	**0.12*****	0.09*	0.05	**0.18*****	**-0.12****
CI	[-0.02 - 0.14]	[0.05 - 0.21]	[-0.06 - 0.10]	[0.05 - 0.20]	[-0.00 - 0.19]	[-0.02 - 0.12]	[0.10 - 0.26]	[-0.22 - -0.02]
HH Decile 3	**0.15*****	**0.19*****	**0.12*****	**0.17*****	**0.18*****	**0.08****	**0.24*****	**-0.22*****
CI	[0.06 - 0.23]	[0.11 - 0.28]	[0.04 - 0.20]	[0.09 - 0.25]	[0.09 - 0.28]	[0.00 - 0.15]	[0.15 - 0.32]	[-0.32 - -0.12]
HH Decile 4	**0.15*****	**0.17*****	**0.20*****	**0.15*****	**0.24*****	**0.09****	**0.32*****	**-0.33*****
CI	[0.06 - 0.24]	[0.08 - 0.25]	[0.11 - 0.28]	[0.07 - 0.23]	[0.14 - 0.34]	[0.02 - 0.17]	[0.23 - 0.40]	[-0.43 - -0.23]
HH Decile 5	**0.19*****	**0.28*****	**0.24*****	**0.25*****	**0.23*****	**0.17*****	**0.41*****	**-0.28*****
CI	[0.10 - 0.27]	[0.20 - 0.37]	[0.15 - 0.32]	[0.17 - 0.33]	[0.13 - 0.32]	[0.09 - 0.25]	[0.32 - 0.49]	[-0.38 - -0.18]
HH Decile 6	**0.15*****	**0.32*****	**0.46*****	**0.31*****	**0.29*****	**0.12*****	**0.41*****	**-0.35*****
CI	[0.06 - 0.24]	[0.23 - 0.41]	[0.37 - 0.54]	[0.23 - 0.40]	[0.19 - 0.39]	[0.04 - 0.20]	[0.32 - 0.49]	[-0.45 - -0.24]
HH Decile 7	**0.25*****	**0.31*****	**0.56*****	**0.31*****	**0.38*****	**0.11****	**0.44*****	**-0.48*****
CI	[0.15 - 0.34]	[0.22 - 0.41]	[0.47 - 0.65]	[0.22 - 0.40]	[0.28 - 0.49]	[0.02 - 0.19]	[0.35 - 0.53]	[-0.58 - -0.37]
HH Decile 8	**0.26*****	**0.32*****	**0.75*****	**0.35*****	**0.49*****	**0.21*****	**0.67*****	**-0.48*****
CI	[0.16 - 0.35]	[0.22 - 0.42]	[0.66 - 0.85]	[0.26 - 0.44]	[0.38 - 0.59]	[0.12 - 0.30]	[0.57 - 0.77]	[-0.59 - -0.37]
HH Decile 9	**0.44*****	**0.41*****	**1.04*****	**0.46*****	**0.54*****	**0.21*****	**0.71*****	**-0.71*****
CI	[0.33 - 0.55]	[0.30 - 0.52]	[0.94 - 1.14]	[0.36 - 0.55]	[0.43 - 0.66]	[0.12 - 0.31]	[0.61 - 0.82]	[-0.83 - -0.59]
HH Decile 10	**0.52*****	**0.28*****	**1.53*****	**0.49*****	**0.71*****	**0.36*****	**0.82*****	**-0.91*****
CI	[0.40 - 0.65]	[0.16 - 0.40]	[1.42 - 1.64]	[0.39 - 0.60]	[0.59 - 0.84]	[0.26 - 0.46]	[0.71 - 0.93]	[-1.04 - -0.79]
Urban	0.01	-0.05	**0.16*****	0.04	**0.15*****	-0.03	**0.09*****	**-0.14*****
CI	[-0.05 - 0.07]	[-0.11 - 0.02]	[0.11 - 0.22]	[-0.01 - 0.10]	[0.09 - 0.22]	[-0.09 - 0.02]	[0.03 - 0.15]	[-0.21 - -0.08]
Observations	196,285	196,285	196,285	196,285	196,285	196,285	196,285	196,285
Survey FE	YES	YES	YES	YES	YES	YES	YES	YES

Equal country weights, ∗,∗∗,∗∗∗ Significant differences between 6-11mth and 18-23mth: ∗P < 0.05, ∗∗P < 0.01, ∗∗∗P < 0.001; 95% CI in brackets

Supplement Table III.3: MDD status by wealth decile

Wealth Decile (1 being poorest, 10 being richest)	% Children Meeting MDD (country weights)	% Children Meeting MDD (equal weights)
1	19.0% [18.6;19.5]	20.7% [20.2;21.2]
2	21.9% [21.4;22.5]	22.8% [22.2;23.3]
3	21.6% [21.0;22.1]	24.4% [23.8;25.0]
4	22.6% [22.1;23.2]	24.8% [24.2;25.4]
5	25.1% [24.5;25.7]	27.9% [27.3;28.6]
6	26.3% [25.7;27.0]	28.4% [27.7;29.0]
7	28.1% [27.4;28.7]	30.4% [29.7;31.0]
8	30.3% [29.6;30.9]	34.3% [33.6;35.0]
9	32.3% [31.5;33.0]	37.0% [36.2;37.7]
10	36.9% [36.1;37.6]	42.2% [41.5;43.0]

Averages with 95% CI in brackets

Supplement Table III.4: MDD status by age group

Age Group	% Children Meeting MDD (country pop. weights)	% Children Meeting MDD (equal country weights)
6-11 months	17.1% [16.8;17.3]	20.6% [20.3;20.9]
12-17 months	29.9% [29.5;30.2]	33.3% [32.9;33.6]
18-23 months	32.3% [31.9;32.7]	33.2% [32.8;33.6]

Averages with 95% CI in brackets

Supplement Figure III.1: Flow diagram showing exclusions, missing data, and final sample size of the study population

N= 710,665 children aged 0-59 months old and alive at the time of the survey with month specific age data

Excluded by design:

- 496,295 children between 0-5 & 24-59 months
- 8,582 children between 6-23 months that were not the youngest child
- 2,174 children not living with their mother in the household

N= 203,614 youngest children aged 6-23 months old at the time of the survey living with their mother

Excluded by missing data:

- 6,100 children without/ with incomplete food group dietary data

Final Sample Food Groups: N= 197,514 children aged 6-23 months with information on food group intake

Final Sample Food Items: N= between 186,928 children aged 6-23 months (Yogurt) and 197,514 (#2 Legumes/nuts, #5 Eggs, #7 Other fruits/vegetables and #8 Breastmilk)

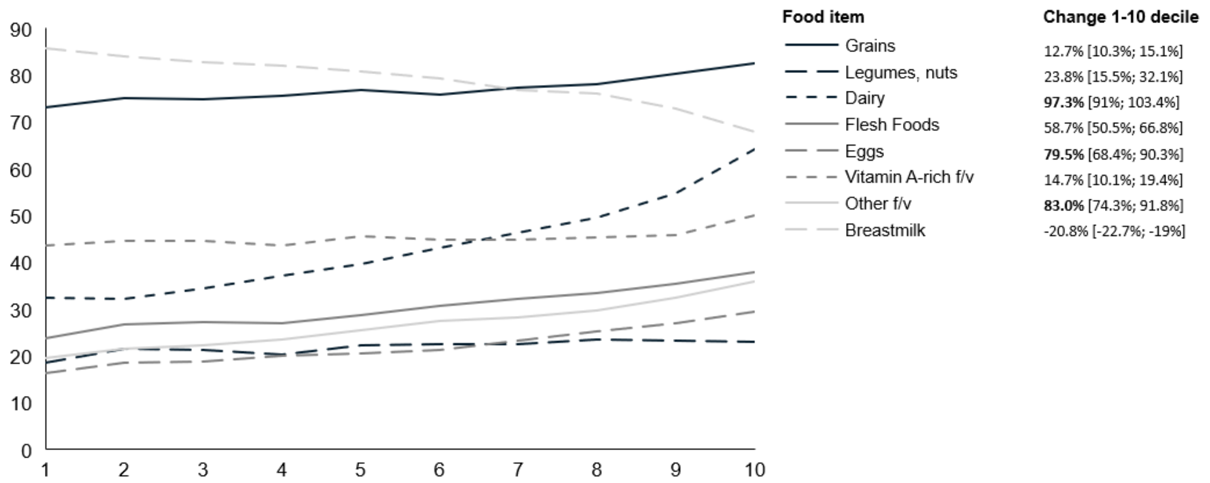
Excluded in regressions:

- 1,229 children without full socio-economic and household data

Final Sample Regression Food Groups: N= 196,285 children aged 6-23 months with information on food group intake

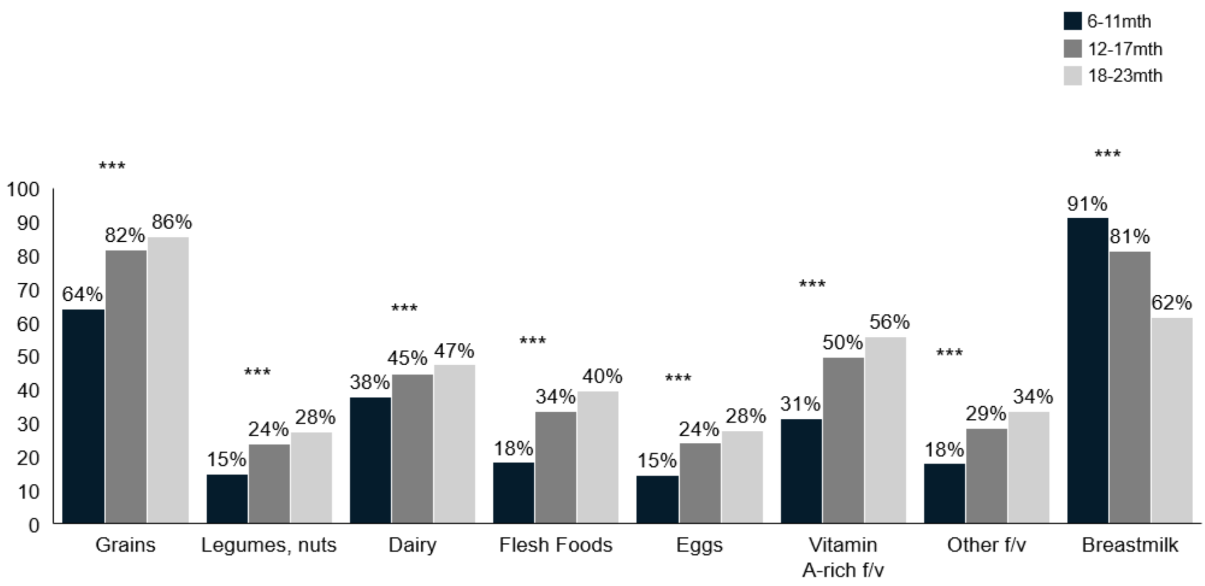
Final Sample Regression Food Items: N ranges between 186,332 children aged 6-23 months (Yogurt) and 196,285 (“Legumes/nuts”, “Eggs”, “Other fruits/vegetables” and “Breastmilk”)

Supplement Figure III.2: Food group consumption levels for different household wealth deciles



Changes in percent with 95% CI in brackets, bold numbers >75%, countries weighted by population size

Supplement Figure III.3: Food group consumption levels for separate age groups



Food group consumption for different age groups, countries weighted by population size, ∗,∗∗,∗∗∗ Significant differences between 6-11mth and 18-23mth: ∗P < 0.05, ∗∗P < 0.01, ∗∗∗P < 0.001.

Chapter IV

The magnitude and depth of child food poverty in low- and middle-income countries: Insights from 200,346 children in 61 countries

With: Sebastian Vollmer

Abstract

The minimum dietary diversity (MDD) is a binary indicator that assesses micronutrient deficiency in young children and is used by UNICEF to determine child food poverty across the globe. We provide a comprehensive view of child food poverty in terms of population shares as well as depth of poverty for children aged 6-23 months using DHS and MICS data from 61 low- and middle-income countries. Across 61 LMICs, the Food Poverty Share stood at 73.7% and the Food Poverty Gap at 35.2%. We show that many children could be relieved from child food poverty by focusing on the children closely below the MDD threshold of consuming five food groups. Children consuming three or four food groups made up between 31.2%- 44.4% of the total child population across different regions. The most relevant food groups separating children consuming only three food groups from those consuming five food groups were fruits and vitamin food groups as well as protein-rich flesh foods. Individual food groups showed different statistical associations with regional availability, a household's wealth quintile, the child's age as well as maternal education. The results suggest that targeted interventions can lead to many more children meeting MDD and that country-specific analyses should be complemented with information on local food prices as well as local food availability.

IV.1 Introduction

According to the WHO, more than 205 million children were undernourished in 2020, most of them living in LMICs.[1] As such, there is yet a long way to go to achieve the Sustainable Development Goal #2 Zero Hunger agenda of alleviating the world of hunger. Child under- and malnutrition are generally measured by two indicators: Anthropometry and diet. While anthropometry considers the weight, height and age of children, a child's diet is commonly assessed by looking at minimum dietary diversity (MDD).[2-3] If a child fails to achieve the consumption of minimum dietary diversity, it is considered to suffer from "child food poverty".[4] Recent literature has put increased emphasis on children's diet and particularly on minimum dietary diversity, as firstly, not reaching minimum dietary diversity has been linked to significantly increased morbidity and mortality and delayed development of the brain and the nervous system.[5-7] Secondly, it has been shown that for young children <24 months, micronutrient diversity has little overlap with children's physical signs of under- and malnutrition. Hence, it requires its own measurement and focus.[2,8]

The WHO defined Minimum Dietary Diversity (MDD) as a binary indicator in 2008 to track children's micronutrient density and as such, allow comparison of feeding practices over place and time. At the age of six months, breastmilk alone is not considered to provide sufficient nutrients anymore. Therefore, appropriate complementary feeding should start with continued breastfeeding for up to two years at least.[9,10] This age is particularly relevant, as poor nutrition during this time has been shown to directly affect subsequent health outcomes such as impairments of cognitive and organ development.[5] The initial MDD indicator was comprised of seven different food groups, out of which at least four had to be consumed over the previous day or night to reach MDD. This definition was revised in 2017, incorporating feeding with breastmilk to account for the fact that breastmilk itself remains important during this age window and that complementary breastfeeding should not replace it fully. According to this revised definition, MDD is achieved when at least five out of eight food groups were consumed over the past 24 hours by the child. These eight food groups are grains/roots/tubers, legumes/nuts, dairy, flesh foods, eggs, Vitamin-A-rich fruits/vegetables, other fruits/vegetables and breastmilk.[11]

Particularly in low- and middle-income countries (LMICS), providing children with sufficient micronutrients is faced with multiple challenges. Several studies have shown that between 73.8% - 77.6% of children across large samples of LMICs did not meet MDD and as such suffered from child food poverty[2,12,13,14]. While regional variation was found, ranging from >=50% of children meeting MDD in South America to <=25% in Africa, significant shares of children did not meet WHOs recommended MDD in all regions.[2,13.14] Consequently, a better understanding of the patterns behind the binary MDD, particularly factors driving high levels of children not meeting MDD and the identification of target groups that can be brought to meeting MDD in fast and cost-efficient ways are of great importance for policymakers worldwide, aiming to eradicate under- and malnutrition across the globe.

Given that MDD is a binary indicator, it lacks information about both food groups specific consumption patterns of children not meeting MDD as well as the depth of child food poverty, i.e., how far apart these children are from the threshold of having consumed at least 5 food groups. While few studies have investigated food group-specific consumption patterns for children not meeting MDD[12,15], only one study has analyzed the depth of child food poverty.[16] This study introduced a methodology that applied the commonly used Foster–Greer–Thorbecke poverty measures to MDD to assess both shares of children suffering from food poverty as well as the magnitude of child food poverty.[17] Their analysis included a sample from 22 Central and West African countries. We argue that to improve the targeting of children in need and track progress made locally as well as globally such an analysis needs to be done for a global sample of LMICs. Building on the approach of assessing food poverty with established measures of poverty, we contribute to the existing literature in three distinct ways. At first, we apply this methodology to a global sample of 61 LMICs that represent ~63% of the global LMICs population. Second, we investigate the distribution of children not meeting MDD and identify promising target groups for cost-efficient interventions. Finally, we analyze which child and household factors are associated with food group-specific consumption for the previously identified sub-populations.

IV.2 Materials and Methods

Empirical Application and Data

For our analyses, we leveraged two types of household survey data, i.e., demographic health surveys (DHS) together with multiple indicator cluster surveys (MICS). The DHS program has been running in seven waves since 1984 and, just like MICS, which was started in 1995, conducts surveys on population, health, and nutrition for nationally representative samples of women of reproductive age and their children in LMICs across the globe[18-19]. Both survey types apply a two-stage stratified sampling design for household selection. Enumeration areas are selected from stratified areas (regions and urban/rural) and subsequently, a fixed number of households is sampled from each enumeration area applying equal probability systematic sampling. We selected the most recent surveys and attained 41 surveys from DHS and 20 MICS surveys yielding a final country sample of 61 LMICs. For Colombia, we used the DHS Wave 6 data from 2010 instead of Wave 7 data from 2015, as it contained many more observations with nutrition data. Additionally, we also included 6 datasets that were in part collected during the time of the COVID-19 pandemic between 2020-2021. Two of these datasets, i.e., from India and Mauritania, were conducted between 2019-2021, while the other 4 datasets from Malawi, Rwanda, Liberia, and Gambia contained interviews that were conducted between 2019- 2020. We are aware that data from these surveys may be subject to the dynamics of the COVID-19 pandemic at the time, which certainly affected nutrition patterns. However, we decided to include them given that many household interviews in these different surveys were conducted prior to the first cases recorded and countermeasures being enacted. Also, we believe that for our analyses, the most current data is preferable compared to data dating multiple years back. Finally, we estimated the total population sizes of children aged 6-23 months by multiplying population data from children aged 0-5 years drawn from the United Nations World Population Prospect with the estimated country-specific share of children aged 6-23 months that we derived from our surveys.

Study Population and Sample Size

We attained nationally representative data for 822,508 children aged 0-5 years. Our sample was restricted to children aged 6-23 months and focused on the youngest children living in the household as recommended by the WHO Indicators for assessing infant and young child feeding practices (IYCF).[11] This left us with 206,500 children. We further excluded children that had missing data on at least one of the food groups (FGs) we investigated. This excluded an additional 6,131 children leaving us with a final sample size of 200,369 for our analyses of food group consumption patterns. For our regressions, we used all available DHS and MICS datasets from after 2010, giving us a sample size of 263,003 children (Supplement Figure 1). Based on the UN Population Prospects population data, the countries in our sample represent 63.1% of the worldwide LMIC's child population between 0-5 years of age. Using the population data of children aged 0-5 years (384.1 million children) and multiplying it with the estimated share of children aged 6-23 months among children aged 0-5 years attained from our surveys (29.5%), our sample consists of an estimated total population of 113.4 million children.

Variables of Interest – Child food poverty and food groups

Food consumption data in both DHS and MICS surveys was recorded as a binary variable (yes, no) based on a 24h recall by the mothers. A total of 17 food items were recorded that we allocated into the eight FGs relevant for MDD and thus, child food poverty (Supplement Figure 2). To avoid confusion around the terminology, we will subsequently refer to children not meeting MDD as children suffering from child food poverty. The relevant eight FGs are: 1. Grains, roots and tubers, 2. Legumes and nuts, 3. Dairy products (milk, yogurt, cheese), 4. Flesh foods (meat, fish, poultry and liver/organ meats), 5. Eggs, 6. Vitamin-A-rich fruits/vegetables, 7. Any other fruits/vegetables, and 8. Breastmilk. Individual missing data points on food item level as well as "don't know" responses were assumed to be a "No" as recommended by DHS[20]. For the different FGs, this applied to 350 responses in our sample of 199,779 observations. Using food item consumption levels, we constructed food group consumption as well as child food poverty as binary variables, assigning "Yes" to food group consumption if at least one of the underlying food items was consumed and "No" if none of the underlying food items for which data was available were consumed. Child food poverty was assigned "Yes" if at least five of the eight FGs were consumed and "No" otherwise.

Analyses

At first, we calculated the share of children consuming a certain number of FGs (i.e., between zero and eight). For our global and regional consumption averages, we applied country weights by using the estimated total population of children aged 6-23 months. As a result, our global and regional consumption estimates were strongly influenced by the largest countries by population in our sample, i.e., India (29.1%), Nigeria (7.9%), Indonesia (6.5%) and Pakistan

(6.4%) together accounting for ~50 percent of the total population size of our sample. We therefore also included results with equal country weights as sanity checks. We then continued to calculate two different food poverty measures as introduced by Vollmer et al. (2023).[16]

$$FPM_\alpha = \frac{1}{n}\sum_{i=0}^{p} w_i \left(\frac{z - x_i}{z}\right)^\alpha$$

Here, z corresponds to the child food poverty threshold (i.e., consumption of five FGs), x_i is the number of FGs consumed by child i, n as the total number of children adjusted for by sample weights, p is the number of children having consumed less than five FGs and w_i is the child-specific sample weight. α is a fixed parameter. Our first food poverty measure (α=0) derives the weighted poverty headcount ratio. This equals to the weighted total share of children suffering from child food poverty (i.e., not meeting MDD). We will subsequently refer to this measure as "Food Poverty Share". Our second food poverty measure (α=1) considers the distance of the malnourished children from the child food poverty threshold and is presented in percent. For children that consumed at least five FGs, this food gap is zero. This second measure informs about the depth of food poverty behind the previous Food Poverty Share. We will subsequently refer to this measure as "Food Poverty Gap". A poverty gap of 40% for example could imply that six out of ten children of the population are "non-poor" and the rest of the child population consumes zero food groups. It could also imply that the entire population is "poor" consuming 40% of the food poverty line, which would translate to two different food groups.

In addition to the two measures of food poverty, we also present consumption levels for each of the individual FGs of children suffering from child food poverty vs. not and specifically those children that are close to the MDD threshold, i.e., who are one or two FGs away from achieving MDD. To better understand the underlying factors explaining the consumption differences around the MDD threshold, we ran logistic regression for each FG, including child and household covariates and country-fixed effects. The sample for the regressions was children that consumed between three and six FGs. We selected this sub-sample to include children that only lack one or two FGs to achieve MDD and to have the same bandwidth around the MDD threshold. We assumed that variation in consumption levels comes from four different sources: General availability, household resources, education/awareness as well as cultural/religious dispositions to consuming certain FGs. The child-specific covariates in our analyses were a child's sex, age in months, the mother's age at birth in years and maternal education level. The household covariates included the household's wealth quintile, urban/rural residency as well as household size. As opposed to the previous analyses where we used the most recent survey, for this analysis, we included all surveys available for the countries in our sample as such constructing a panel over time with much more variation. In a second step, we included a household's religion into the regression, which we used as a proxy for cultural differences beyond country FEs driving variation in food group consumption patterns. For this, we assigned households to 9 major religious movements, i.e., Christianity, Islam, Hinduism, Buddhism, Animism/traditional, Sikh, Jewish, No Faith and Other. Our results are presented with 95% confidence intervals, and we included standard errors in brackets. The analyses were conducted with Stata version 16.0.

IV.3 Results

Share of food group consumption levels and MDD

We found that an estimated 73.7% [73.5%-73.9%] of children across the 61 LMICs, translating to an estimated population of 83.6 million children, consume less than five FGs and as such do not meet the WHO's recommended MDD and suffer from child food poverty (Table 1). Looking at those children that did not meet MDD, it is noteworthy that both the share of children only consuming three (22.1%) as well as four FGs (19.0%) was close to the share of all children meeting MDD (26.3%) (Table 1). This implies that adding just one or two FGs to the diet of children not meeting MDD in our sample has the potential of alleviating an estimated 46.6 million children of insufficient dietary diversity. Applying equal country weights shows similar results and confirms the overall picture, i.e., that there are many children in LMICs with unmet dietary needs. Results on a country level can be found in the Appendix (Supplement Table 1).

Food Poverty Share, Food Poverty Gap and Average Missing Food Groups

Table 2 presents our food poverty measure results for each country, region and pooled sample together with the average number of FGs that children that suffer from child food poverty are missing. Across all countries, 73.7% suffered from child food poverty (Measured by FP-Share) and the FP-Gap was 35.2% with 2.4 average missing FGs. At the same time, there was substantial inter-country variation. In Peru, 27.8% of children suffered from child food poverty, there was a

FP- Gap of 9.7% and children not meeting MDD consumed on average 3.3 FGs, implying missing food group consumption of 1.7 FGs. In Burkina Faso, 95.1% of children suffered from child food poverty, there was a FP-Gap of 54.4% and on average, children that did not meet MDD were missing 2.9 FGs.

Table IV.1: Share of children consuming different levels of food groups

		With Pop. Weights		Without Pop. Weights	
No of FG	Observations	Percent	Cum	Percent	Cum
0	2,154	0.9	0.9	0.9	0.9
1	25,676	12.9	13.8	10.1	11.0
2	35,623	18.8	32.6	17.6	28.6
3	43,357	22.1	54.7	22.1	50.7
4	38,527	19.0	73.7	20.4	71.1
5	26,818	13.3	87.0	14.6	85.7
6	15,893	7.6	94.6	8.7	94.4
7	8,450	3.8	98.4	4.3	98.7
8	3,871	1.7	100.0	1.3	100.0
Total	200,369	100.0		100.0	

FG: Food Groups

The intra-country relationship between FP-Share scores and FP-Gap scores also showed variation. Countries such as Timor-Leste, Benin and Guinea showed relatively high FP-Gap levels and average missing FGs compared to other countries with similar FP-Share levels, while countries such as Burundi, Rwanda and Tanzania showed relatively low levels of FP-Gaps and average missing FGs compared to other countries with similar FP-Shares. Comparing results on a regional level, we found that the number of children suffering from child food poverty varied substantially, ranging from 58.7% children in South America to 22.3% in Africa. At the same time, the Food Poverty Gap was consistently less than half of the Food Poverty Share, implying larger shares of children suffering from child food poverty being close to the MDD threshold in all regions. This is confirmed by the similar average number of missing FGs ranging from 2.4 in Asia to 1.8 in South America. Plotting the distribution of children lacking just one or two FGs across regions, we found that shares were around 40% in Africa, Asia and Europe and 32.2% in South America (Supplement Figure 3). While the share of children closely below the MDD threshold showed similar patterns across regions, our results also show that Asia and Africa have especially much to gain by successfully lifting these children above the bar as this would more than double (Asia) and even triple (Africa) the number of children meeting MDD (and as such not suffering from child food poverty). Given that these are the highly populated regions across LMICs, advances in these regions would have large effects on the global share of children suffering from child food poverty.

Table IV.2: Food Poverty Share, Gap and Average Missing Food Groups by country and region

Country	FP-Share Percent	FP-Gap Percent	Average Missing FGs	Country	FP-Share Percent	FP-Gap Percent	Average Missing FGs
Albania	47.7	21.2	2.2	Liberia	91.6	45.5	2.5
Angola	71.4	33.9	2.4	Madagascar	70.7	27.9	2.0
Armenia	63.8	23.6	1.9	Malawi	81.3	33.5	2.1
Bangladesh	64.5	25.9	2.0	Maldives	29.0	10.2	1.8
Benin	75.0	41.9	2.8	Mali	78.9	41.1	2.6
Burkina Faso	95.1	54.4	2.9	Mauritania	79.9	39.5	2.5
Burundi	82.4	32.2	2.0	Mozambique	71.9	33.9	2.4
Cambodia	59.4	23.0	1.9	Myanmar	78.9	37.1	2.4
Cameroon	81.9	36.0	2.2	Namibia	76.5	40.1	2.6
Central Afr. Rep.	88.9	47.1	2.6	Nepal	56.7	21.9	1.9
Chad	76.6	39.9	2.6	Niger	91.9	51.8	2.8
Colombia	38.2	13.4	1.8	Nigeria	77.3	35.9	2.3
Comoros	78.2	36.7	2.3	Pakistan	85.0	40.5	2.4
Congo	86.1	40.3	2.3	Peru	27.8	9.7	1.7
Congo (Dem. Rep.)	82.8	37.7	2.3	Rwanda	65.6	23.1	1.8
Cote d'Ivoire	77.8	34.6	2.2	Sao Tome & Princ	65.2	29.0	2.2
Dominican Rep.	48.7	17.8	1.8	Senegal	80.7	38.6	2.4
Egypt	65.3	29.6	2.3	Sierra Leone	74.9	35.8	2.4
Ethiopia	86.5	45.1	2.6	South Africa	61.0	27.5	2.3
Gabon	81.8	37.1	2.3	Tajikistan	77.7	37.1	2.4
Gambia	79.9	36.5	2.3	Tanzania	78.5	30.3	1.9
Ghana	76.6	35.6	2.3	Timor-Leste	72.6	39.2	2.7
Guatemala	40.7	15.2	1.9	Togo	81.0	33.9	2.1
Guinea	86.2	48.7	2.8	Uganda	68.3	27.5	2.0
Guinea-Bissau	90.9	47.7	2.6	Yemen	78.5	35.0	2.2
Guyana	59.7	23.7	2.0	Zambia	76.6	31.8	2.1
Haiti	81.0	36.6	2.3	Zimbabwe	82.9	34.1	2.1
Honduras	41.6	15.4	1.9				
India	76.6	40.0	2.6	**Africa**	77.8	36.5	2.3
Indonesia	45.7	17.1	1.9	**Asia**	72.1	35.2	2.4
Jordan	65.8	28.2	2.1	**Europe**	56.7	22.6	2.0
Kenya	63.9	26.0	2.0	**South America**	41.3	15.5	1.8
Kyrgyz Republic	40.0	13.9	1.7	**Total***	73.7	35.2	2.4
Lesotho	83.3	36.3	2.2	**Total****	71.2	32.5	2.2

FP= Food Poverty, FGs = Food Groups
* Country Pop Weights, ** Equal Country Weights

Missing food groups for children by child food poverty status

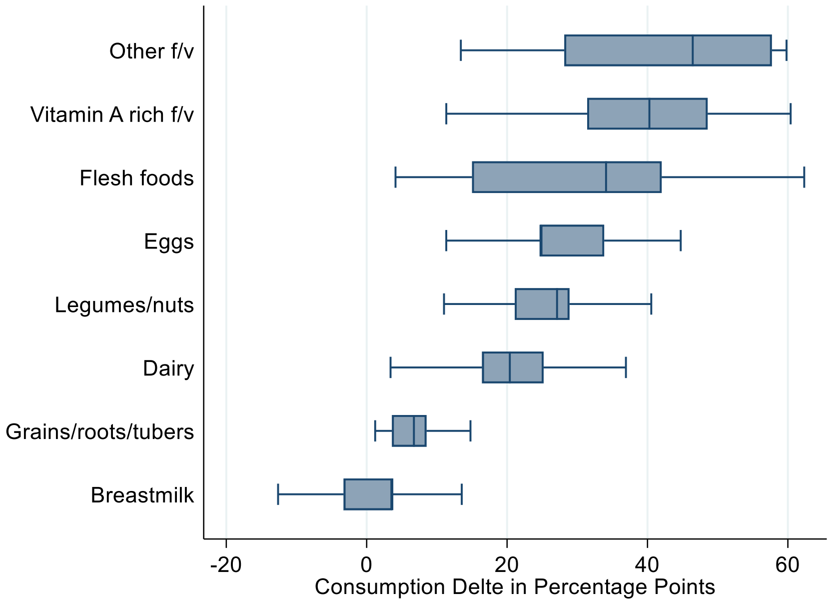
Having established that there are many children suffering from child food poverty and that relevant shares of these children only lacked one or two FGs, we took a closer look at food group-specific consumption levels. We found that particularly “2. Legumes/nuts” and “5. Eggs” are FGs that not only children suffering from child food poverty least often consumed but also those children that did not (Table 3). The largest difference in consumption levels between children suffering from child food poverty vs. not was for “7. Other fruits/vegetables” with 32.7% vs. 87.7% of children not having consumed the food group. Having established previously that much is to gain by lifting children consuming three or four FGs above the MDD threshold, we also examined which FGs separated children consuming exactly five vs. three FGs. We found that the largest consumption differences with more than 30 percentage points (pp.) appeared for “7. Other fruits/vegetables” with a difference of 42.2pp., “6. Vitamin-A rich f/v” with a 38.2pp., and “4. Flesh Foods” with a 35.0pp. higher consumption rate for children consuming five FGs compared to children consuming only three FGs. Overall, it seems that particularly a diverse consumption of fruits and vegetables, as well as protein rich foods, was a main separating factor for children ranging from consumption of three to five FGs. This is confirmed when plotting country-specific consumption level differences between children consuming five FGs vs. those consuming three FGs (Figure 2).

Table IV.3: Missing consumption of FGs child food poverty status number of FGs consumed

	No Child Food Poverty Percent	Child Food Poverty Percent	5 FG Percent	3 FG Percent
Legumes/nuts	46.7	88.9	61.3	87.5
	[46.0 - 47.4]	[88.6 - 89.2]	[60.3 - 62.4]	[86.9 - 88.1]
Eggs	43.2	90.4	60.6	89.7
	[42.5 - 44.0]	[90.1 - 90.7]	[59.6 - 61.7]	[89.1 - 90.3]
Flesh Foods	33.1	83.0	45.8	80.8
	[32.4 - 33.8]	[82.6 - 83.3]	[44.7 - 46.8]	[80.1 - 81.4]
Other fruits/veg.	32.7	87.7	45.9	88.1
	[32.0 - 33.5]	[87.4 - 88.0]	[44.8 - 46.9]	[87.5 - 88.6]
Dairy	29.9	67.3	39.2	60.9
	[29.3 - 30.6]	[66.9 - 67.7]	[38.2 - 40.2]	[60.0 - 61.7]
Breastmilk	20.5	22.3	21.8	22.0
	[19.9 - 21.1]	[21.9 - 22.7]	[21.0 - 22.7]	[21.3 - 22.8]
Vitamin-A rich f/v	14.8	68.6	22.3	60.5
	[14.3 - 15.4]	[68.2 - 69.1]	[21.4 - 23.2]	[59.6 - 61.3]
Grains/roots/tubers	2.1	30.2	3.0	10.6
	[1.9 - 2.3]	[29.8 - 30.7]	[2.7 - 3.4]	[10.0 - 11.1]
Observations	55,032	145,337	26,818	43,357

MDD: Minimum Dietary Diversity, FG: Food Groups, Weighted by Pop Weights AND Country Size, 95% CI in brackets

Figure IV.1: Country-level FG consumption increases between consumption of 3 to 5 FGs



Weighted by Pop Weights AND Country Size. The box boundaries represent the 25th and 75th quantile; the line represents the median.

Factors affecting consumption levels around the MDD threshold

Investigating which factors were associated with consumption differences for our FGs excluding breastfeeding, we found that the child's age as well as maternal education showed significant coefficients for most FGs, particularly when moving from no education to secondary or higher education (Table 4). For "2. Legumes/nuts", consumption was negatively associated with higher education, which may be related to matters of availability in urban areas that in themselves tend to be wealthier and imply that the increase in consumption of legumes/nuts in the group of children consuming between three and six FGs is driven by poorer more rural areas.

A household wealth position also showed significant associations with those FGs that tend to be associated with higher prices per calorie, such as "3. Flesh Foods" and "5. Eggs" and particularly high coefficients for Dairy as a household reached the top two wealth quintiles. Interestingly, rural residency was associated with increased Legumes/nuts consumption while it was associated with decreased consumption of Flesh Foods. For FGs "3. Dairy" and "5. Eggs" it was even more relevant. Here, urban residency implied more than 20pp. higher odds of consuming the respective FGs.

Table IV.4: Regression results of child and household characteristics on food group consumption level for children consuming between 3-6 FGs

	FGs	Grains	Legumes, nuts	Dairy	Flesh foods	Eggs	Vitamin-A-rich f/v	Other f/v
Availability	**Rural (base Urban)**	-0.00	**0.13*****	**-0.23*****	**-0.07*****	**-0.21*****	0.05	-0.04
	CI	[-0.11 - 0.10]	[0.07 - 0.19]	[-0.29 - -0.17]	[-0.13 - -0.02]	[-0.27 - -0.15]	[-0.01 - 0.10]	[-0.10 - 0.01]
Household Resources	***HH Wealth Quintile (base lowest quintile)***							
	HH Decile 2	0.04	0.03	0.03	**0.11*****	**0.10*****	0.04	**0.14*****
	CI	[-0.06 - 0.14]	[-0.03 - 0.09]	[-0.04 - 0.09]	[0.06 - 0.17]	[0.03 - 0.17]	[-0.02 - 0.10]	[0.08 - 0.20]
	HH Decile 3	-0.06	**0.08****	**0.21*****	**0.22*****	**0.17*****	**0.09*****	**0.30*****
	CI	[-0.16 - 0.04]	[0.01 - 0.15]	[0.14 - 0.27]	[0.16 - 0.28]	[0.10 - 0.24]	[0.03 - 0.16]	[0.23 - 0.36]
	HH Decile 4	0.01	-0.00	**0.51*****	**0.26*****	**0.28*****	0.03	**0.43*****
	CI	[-0.10 - 0.11]	[-0.07 - 0.07]	[0.44 - 0.58]	[0.20 - 0.33]	[0.20 - 0.36]	[-0.04 - 0.10]	[0.36 - 0.50]
	HH Decile 5	-0.00	0.01	**1.12*****	**0.30*****	**0.46*****	0.01	**0.56*****
	CI	[-0.14 - 0.14]	[-0.08 - 0.09]	[1.03 - 1.21]	[0.22 - 0.38]	[0.37 - 0.55]	[-0.07 - 0.08]	[0.47 - 0.64]
Education and Awareness	**Age of child in months**	**0.04*****	**0.04*****	0.00	**0.08*****	**0.04*****	**0.04*****	**0.05*****
	CI	[0.04 - 0.05]	[0.03 - 0.04]	[-0.00 - 0.01]	[0.08 - 0.08]	[0.04 - 0.05]	[0.04 - 0.05]	[0.04 - 0.05]
	Maternal Education (base no education)							
	Primary education	0.07	**-0.07****	0.01	**0.07****	**0.26*****	-0.00	**0.16*****
	CI	[-0.02 - 0.16]	[-0.13 - -0.01]	[-0.05 - 0.07]	[0.02 - 0.13]	[0.19 - 0.33]	[-0.06 - 0.06]	[0.10 - 0.23]
	Secondary education or higher	**0.17*****	**-0.08****	**0.48*****	**0.20*****	**0.36*****	0.05*	**0.32*****
	CI	[0.05 - 0.28]	[-0.15 - -0.01]	[0.41 - 0.54]	[0.13 - 0.26]	[0.28 - 0.43]	[-0.01 - 0.11]	[0.25 - 0.39]
Others	**Female Sex**	-0.02	-0.00	0.02	-0.01	-0.02	-0.02	0.00
	CI	[-0.09 - 0.05]	[-0.04 - 0.04]	[-0.03 - 0.06]	[-0.05 - 0.03]	[-0.06 - 0.03]	[-0.06 - 0.02]	[-0.04 - 0.04]
	Household Size	0.01	**0.01*****	0.00	**-0.01****	-0.01	-0.00	**-0.01*****
	CI	[-0.01 - 0.02]	[0.00 - 0.01]	[-0.01 - 0.01]	[-0.01 - -0.00]	[-0.01 - 0.00]	[-0.01 - 0.00]	[-0.01 - -0.00]
	Age at mother at birth in years	0.00	-0.00	-0.00	-0.00	**-0.01*****	**0.01*****	0.00
	CI	[-0.00 - 0.01]	[-0.00 - 0.00]	[-0.00 - 0.00]	[-0.00 - 0.00]	[-0.01 - -0.00]	[0.00 - 0.01]	[-0.00 - 0.01]

Equal country weights, ∗P < 0.05, ∗∗P < 0.01, ∗∗∗P < 0.001; 95% CI in brackets, n= 160,029 observations from 55 countries

At the same time, neither a child's sex, the mother's age at birth nor household size seemed to play a significant role in food group consumption patterns. Comparing coefficient sizes, we found that maternal education, as well as awareness for early childhood dietary needs (measured by a child's age in months), together seemed to be most relevant for FGs "1. Grains/roots", "4. Flesh foods" and "6. Vitamin-A rich f/v". Given that the age range of the children in the sample was from 6-23 months, age overall seemed to be an important factor.

We also included religion as a cultural proxy for a subset of 46 countries, for which data on religion was available (Supplement Table 2). Results for our previous controls remained consistent with slight decreases in coefficient sizes. The most notable change was that education started to become significantly associated with increased consumption of food group "Vitamin A rich f/v". Overall, religion only showed statistically significant associations for FGs "3. Dairy" and "4. Flesh Foods" and "5. Eggs", as one would have expected, as well as "7. Other fruits vegetables".

Finally, we compared results for the full sample of children consuming between zero and eight FGs (Supplement Table 3). Results were similar for FGs "3. Dairy", "4. Flesh Foods", "5. Eggs", and "7. Other fruits/vegetables" with slightly larger coefficients. For the remaining FGs "1. Grains/roots", "2. Legumes/nuts" and "6. Vitamin-A rich f/v", wealth quintile was significant and in the case of "6. Vitamin-A rich f/v", also for education. For "2. Legumes/nuts", more educated and rural households seemed to have a higher likelihood to consume these foods.

IV.4 Discussion

Our study confirms the previously reported magnitude of child malnutrition, particularly across LMICs by showing that across our sample of 61 LMICs, roughly 73.7% of children aged 6-23 months did not meet the WHO's minimal dietary diversity requirement translating to ~83.6 million children suffering from child food poverty.[2,12,13,14] Our results also confirm that for a global sample, by applying poverty measures to dietary diversity, researchers can generate important insights into patterns behind the binary outcome of MDD. For countries with higher FP-Gap levels compared to countries with similar FP-Share levels such as Burkina Faso, additional resources may be required to achieve similar results of lifting children above the MDD threshold of five FGs. At the same time, countries with relatively low FP-Gap levels compared to countries with similar FP-Share levels, such as Rwanda, may find it easier to lift larger shares of children above the MDD threshold with a fixed amount of resources. While low FP-Gaps may be related to a country's own food production and fertility of the land, they could also point towards countries that were able to successfully adopt policies facilitating equitable access to different FGs and as such serve as best-practice examples for other countries. In the case of Rwanda, for example, programs like the Health Food Security and Livelihoods Program (FSLP) have shown promising results in increasing household food security and overall consumption and as such may have contributed to an overall smaller gap.[21] Comparing our child food poverty measure results to income poverty measures from 2018 (applying 3.65 USD in 2017 PPP as poverty line), income poverty measures were on average lower, ranging from 71% in LICs to 30% in LMICs for Poverty Headcount Shares and 35% in LICs to 10% in LMICs for Poverty Gaps.[22] This underscores the magnitude of child food poverty across LMICs and confirms the need for broad action to achieve SDG #2 Zero Hunger.

Across regions, the distribution of children suffering from child food poverty was tilted towards the right side, i.e., a majority share of children was closer to achieving MDD than consuming up to two FGs. This is also reflected by the fact that, on average, missing FGs were consistently below 2.5 in all regions. This shows that focusing efforts and resources on children consuming between three and four FGs is a promising approach to relieve a majority share of children from child food poverty while allowing to focus effort and resources on the provision of a reduced set of FGs and items. The FGs that were most relevant in separating children suffering from child food poverty vs. not as well as children consuming only three FGs vs. consuming at least five FGs were the fruits and vegetable FGs as well as "4. Flesh Foods". This underscores further the need for action as these FGs are vitamin dense and protein-rich FGs.[23-25]

Looking at what factors were associated with the consumption of these FGs for children around the MDD threshold, we found that consumption was significantly associated with different mechanisms from availability (measured by urban/rural), household resources, as well as education and awareness. Depending on the food group, different factors were more relevant, highlighting the need to implement different measures depending on which food group consumption policymakers may want to address. The fruits and vegetables groups, as well as protein-rich flesh foods, showed the largest consumption differences between children consuming three and five FGs. For "4. Flesh Foods" and "7. Other fruits/vegetables", both measures around education and awareness as well as financial support may show promising results, while for FGs “6. Vitamin a rich f/v”, measures addressing general availability in a country complemented with awareness programs of early childhood dietary needs may lead to higher probabilities of consumption.[26-28] Overall, incorporating religion did not have much of an effect on other coefficients or the remaining country fixed effects. We cautiously interpret this as a sign that food group consumption patterns are less driven by religious or cultural reasons but rather by the mechanisms our model already incorporated.

It is important to understand which of the different potential mechanisms are at play, i.e., availability, household resources, education/awareness, or cultural/religious habits, to craft most effective and cost-efficient policies. Based on our results, it seems that across LMICs, barriers to consumption are often less culturally determined but more linked to availability, specifically food supply chains, as well as household resources and awareness of children’s early nutrient needs. Associations slightly differed for our focus sample of children around the MDD threshold compared to the overall sample, highlighting the need to identify proper target groups and investigate them separately. Finally, it is important to note that consumption patterns showed large variations across regions and countries, which is why it is important for policymakers to look at local data and understand the local context. Our country fixed effects remained large, implying that local cultural context, exact pricing mechanisms, matters of distribution, seasonality, and supply chain, as well as equality in access to different FGs, could also play important roles.[29-31] Attaining more granular data, particularly on local prices and availability will be important going forward to enable policymakers to better determine the precise mechanisms driving food group consumption and thus craft targeted interventions.[32]

Limitations

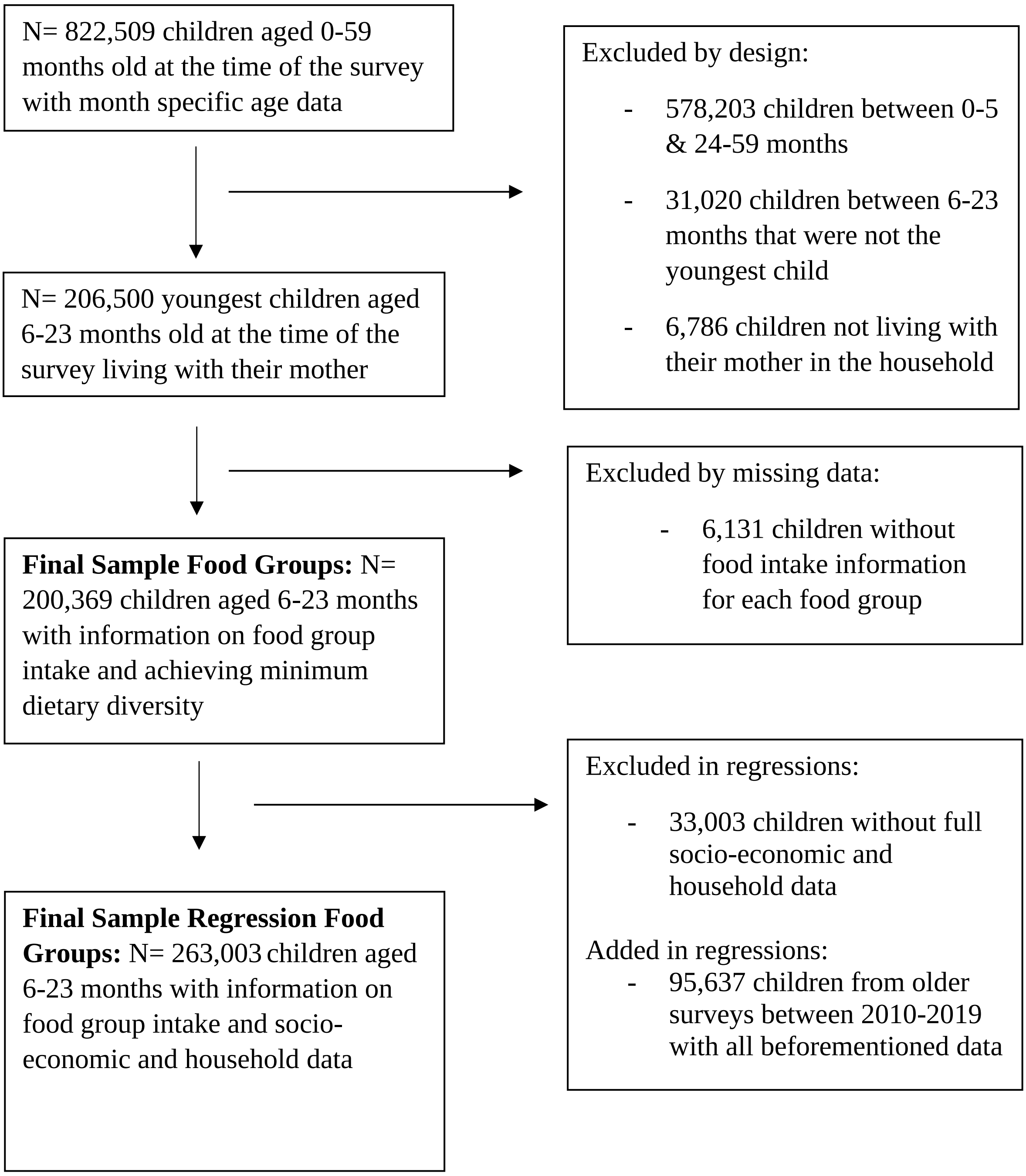
There are a few data limitations in our analyses. Firstly, using food consumption data that is based on self-reported 24h recall is subject to a certain degree of measurement error that can, for instance, be due to different consumption patterns during different days of interviewing as well as lack of memory of all food consumed. While these issues would be most relevant on an individual level, food intake data has been found to be appropriate at the population level.[33] Another limitation that we had was that we did not know anything about the exact quantities of food items consumed. This would add much more precision to children’s actual micronutrient intake. However, unfortunately, to the best of our knowledge, this data does not exist for such a large sample, and we also do not believe that it would have altered our general findings, i.e., that many children in LMICs suffer from inadequate dietary diversity, that a large potential for increasing children with MDD lies in the children consuming only three or four FGs and that main separating FGs are fruits/ vegetables and protein-rich FGs.

IV.5 Conclusion

Child food poverty shows large a prevalence in LMICs both in terms of headcount as well as depth. Using commonly established poverty measures to investigate child food poverty adds important insights to researchers and policymakers trying to fight under- and malnutrition across the globe. Putting a focus on children close to the minimum dietary diversity (MDD) threshold of consuming more than five out of eight food groups can significantly reduce the share of children suffering from child food poverty, particularly in high-population regions Africa and Asia. To properly craft cost-efficient and effective policy interventions on a national level, researchers and policymakers need to investigate food group consumption patterns and specifically address the factors education/awareness and household resources while ensuring availability.

IV.6 Appendix

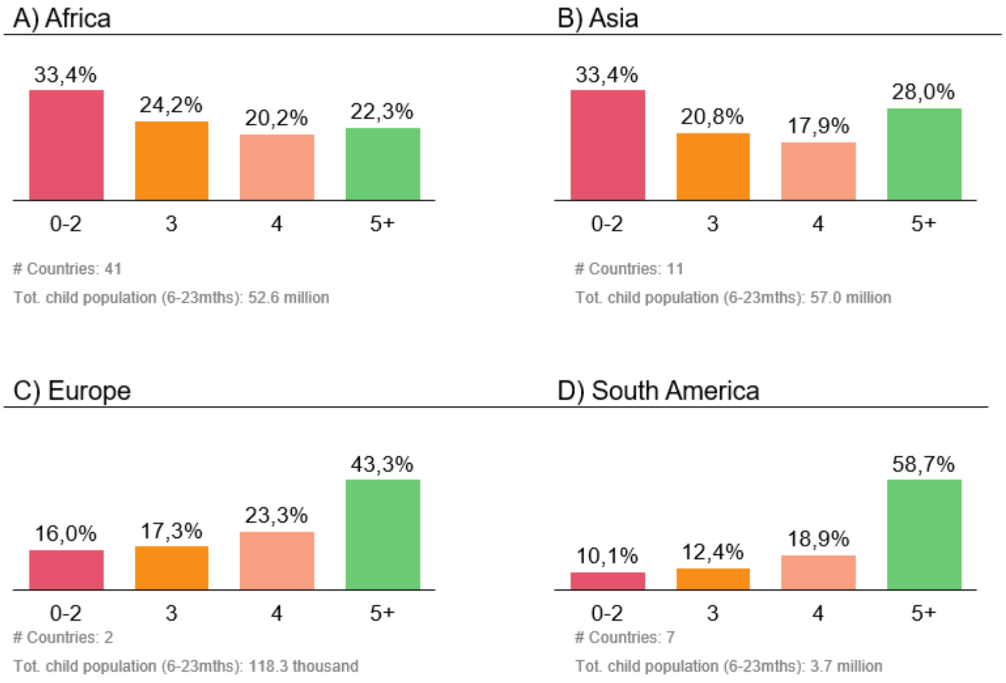
Supplement Figure IV.1: Flow diagram showing exclusions, missing data, and final sample size of the study population



Supplement Figure IV.2: DHS food items according to WHOs MDD food group categories

Food Groups as considered by WHO	Food items collected by DHS
Food Group #1 **Grains, roots and tubers**	1.1 Commercially fortified cereal (baby food) 1.2 Bread, rice, noodles, or foods made from grains 1.3 White potatoes, white yams, manioc, cassava, or any other foods made from roots
Food Group #2 **Legumes, nuts**	2.1 Beans, peas, lentils, or nuts
Food Group #3 **Dairy products**	3.1 Powdered, tinned milk or fresh animal milk 3.2 Infant formula 3.3 Yogurt 3.4 Cheese or other milk products
Food Group #4 **Flesh foods**	4.1 Any meat (beef, pork, lamb, goat, chicken or 4.2 Liver, heart, other organ meats 4.3 Fresh or dried fish or shellfish
Food Group #5 **Eggs**	5.1 Eggs
Food Group #6 **Vitamin A rich fruits/vegetables**	6.1 Pumpkin, carrots, squash or sweet potatoes 6.2 Any dark green leafy vegetables 6.3 Ripe mangoes, papayas, other vitamin A fruit
Food Group #7 **Other fruits/vegetables**	7.1 Other fruits or vegetables
Food Group #8 **Breastmilk**	8.1 Currently breastfeeding

Supplement Figure IV.3: Share of children by number of food groups consumed per region



Applying Country Pop Weights

Supplement Table IV.1: Percent of children by number of food items consumed for 61 LMICs

	MDD-					MDD+			
Countries	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
India	1.5%	19.4%	19.3%	20.3%	15.9%	10.7%	6.1%	3.7%	3.0%
Nigeria	0.4%	12.2%	19.9%	23.8%	20.9%	12.5%	6.1%	3.3%	0.7%
Indonesia	0.1%	2.8%	8.7%	13.6%	20.4%	22.3%	18.8%	10.0%	3.1%
Pakistan	0.4%	12.3%	25.8%	27.8%	18.8%	10.2%	3.9%	0.7%	0.3%
Congo (Dem. Rep.)	0.4%	11.9%	19.7%	29.0%	21.8%	12.2%	3.2%	1.4%	0.3%
Ethiopia	1.5%	17.8%	26.8%	26.0%	14.4%	8.9%	3.0%	1.3%	0.2%
Bangladesh	0.1%	6.1%	12.1%	22.0%	24.1%	19.7%	10.9%	4.2%	0.8%
Egypt	0.4%	10.7%	15.2%	18.3%	20.7%	17.5%	11.1%	4.9%	1.1%
Tanzania	0.3%	2.5%	16.3%	31.2%	28.1%	14.5%	5.4%	1.4%	0.3%
Niger	1.4%	23.2%	36.0%	20.3%	11.0%	4.8%	1.8%	1.2%	0.3%
Kenya	0.5%	6.1%	12.3%	21.3%	23.8%	18.9%	11.6%	3.6%	2.0%
Uganda	0.4%	5.9%	12.5%	25.4%	24.1%	16.4%	8.7%	4.9%	1.6%
Burkina Faso	0.7%	25.6%	39.5%	18.4%	10.9%	3.8%	0.6%	0.4%	0.1%
South Africa	1.6%	6.1%	15.4%	20.6%	17.1%	13.8%	14.5%	9.0%	1.9%
Angola	2.8%	10.7%	16.4%	21.4%	20.0%	12.3%	7.5%	5.9%	3.0%
Mozambique	1.1%	10.3%	17.7%	27.2%	15.7%	10.1%	7.6%	6.9%	3.5%
Myanmar	0.6%	11.5%	22.5%	24.8%	19.5%	11.4%	6.4%	2.4%	0.8%
Madagascar	0.7%	4.7%	13.6%	24.8%	26.9%	17.3%	9.7%	2.3%	0.1%
Ghana	0.2%	10.2%	22.5%	24.8%	18.9%	14.1%	7.0%	1.8%	0.4%
Colombia	0.3%	2.3%	5.3%	10.3%	20.1%	25.6%	23.4%	10.1%	2.7%
Yemen	0.3%	7.8%	21.9%	27.9%	20.6%	13.1%	5.9%	2.0%	0.4%
Cameroon	1.1%	10.0%	17.7%	28.2%	24.8%	11.5%	4.3%	1.8%	0.5%
Cote d'Ivoire	0.4%	10.3%	19.2%	24.7%	23.3%	14.1%	6.3%	1.9%	0.0%
Mali	1.2%	21.6%	18.3%	20.0%	17.5%	11.9%	5.3%	3.0%	1.2%
Cambodia	0.2%	4.4%	10.5%	20.3%	24.0%	22.9%	12.9%	3.6%	1.1%
Peru	0.2%	2.2%	3.1%	7.2%	15.2%	23.8%	23.3%	19.2%	5.9%
Malawi	0.2%	5.8%	18.3%	31.4%	25.5%	12.9%	4.2%	1.3%	0.4%
Zambia	0.5%	5.9%	16.8%	28.6%	24.6%	14.4%	6.3%	2.6%	0.2%
Nepal	0.1%	4.2%	10.1%	19.8%	22.6%	21.9%	14.0%	5.7%	1.7%
Senegal	0.5%	13.4%	23.3%	23.4%	19.9%	12.6%	5.9%	0.9%	0.1%
Chad	1.8%	17.9%	21.7%	19.1%	16.2%	11.4%	6.4%	3.6%	2.0%
Zimbabwe	0.8%	4.2%	18.9%	33.8%	25.2%	12.3%	4.0%	1.6%	0.2%
Guatemala	0.0%	4.9%	4.4%	11.6%	19.8%	24.9%	20.5%	10.9%	3.0%
Burundi	0.2%	6.3%	14.0%	31.3%	30.7%	13.5%	3.3%	0.6%	0.3%
Rwanda	0.1%	4.0%	8.3%	21.0%	32.1%	22.4%	8.6%	2.8%	0.8%
Benin	2.1%	23.5%	19.3%	16.8%	13.1%	9.4%	7.7%	4.9%	3.2%
Guinea	3.5%	22.2%	28.6%	19.4%	12.5%	7.0%	5.0%	1.4%	0.4%
Tajikistan	0.8%	12.2%	21.0%	26.2%	17.3%	13.2%	6.7%	2.2%	0.3%
Togo	0.2%	8.4%	19.4%	23.2%	29.7%	12.7%	5.6%	0.7%	0.0%
Haiti	0.3%	8.9%	22.4%	29.3%	20.1%	12.4%	4.8%	1.7%	0.3%
Sierra Leone	0.9%	11.8%	21.8%	21.4%	19.1%	12.3%	7.3%	3.9%	1.7%
Dominican Rep.	0.4%	1.7%	8.5%	16.6%	21.5%	20.7%	19.0%	10.1%	1.6%
Jordan	0.7%	6.6%	15.8%	20.5%	21.8%	17.7%	9.3%	5.9%	1.7%
Honduras	0.4%	2.8%	6.0%	13.5%	18.9%	25.6%	20.3%	9.9%	2.5%
Namibia	1.5%	20.0%	18.6%	20.9%	15.5%	11.2%	8.0%	3.2%	1.1%
Congo	1.5%	9.4%	26.5%	28.1%	20.6%	10.2%	2.6%	0.7%	0.4%
Kyrgyz Republic	0.0%	2.9%	6.1%	8.8%	22.1%	31.4%	18.6%	9.3%	0.8%
Central African Rep.	4.1%	15.7%	28.7%	25.4%	14.9%	6.1%	3.4%	1.4%	0.2%
Liberia	1.0%	20.8%	20.4%	28.2%	20.9%	6.1%	1.2%	1.1%	0.2%
Mauritania	1.6%	15.7%	20.9%	22.2%	19.4%	12.0%	5.0%	2.4%	0.8%
Gabon	2.2%	6.8%	25.2%	24.4%	23.2%	9.6%	5.7%	2.8%	0.1%
Gambia	0.2%	7.9%	26.2%	25.3%	20.1%	12.5%	6.3%	1.3%	0.1%
Guinea-Bissau	1.4%	18.8%	30.9%	23.8%	16.1%	5.9%	2.6%	0.6%	0.0%
Lesotho	3.3%	5.9%	18.9%	29.6%	25.7%	11.3%	3.7%	1.7%	0.0%
Armenia	0.2%	4.0%	10.3%	20.9%	28.4%	21.3%	10.5%	3.8%	0.5%
Albania	0.6%	8.2%	9.2%	12.7%	16.8%	16.6%	15.8%	14.2%	5.9%
Timor-Leste	3.3%	18.5%	18.6%	17.3%	14.8%	9.2%	7.4%	7.5%	3.3%
Comoros	1.8%	11.1%	18.1%	28.7%	18.6%	10.3%	6.7%	3.5%	1.4%
Guyana	0.2%	6.0%	10.9%	18.5%	24.1%	19.6%	13.1%	5.4%	2.1%
Maldives	0.8%	0.6%	4.5%	8.2%	15.0%	20.6%	24.0%	18.4%	8.2%
Sao Tome & Princ.	0.8%	10.2%	11.8%	22.2%	20.2%	21.7%	8.9%	3.6%	0.6%
Total I*	0.9%	12.9%	18.8%	22.1%	19.0%	13.3%	7.6%	3.8%	1.7%
Total II**	0.9%	10.1%	17.6%	22.2%	20.4%	14.5%	8.7%	4.3%	1.3%

* Country Pop Weights
** Equal Country Weights

Supplement Table IV.2: Regression results food group consumption levels for children consuming between 3-6 FGs including religion

	FGs	Grains	Legumes, nuts	Dairy	Flesh foods	Eggs	Vitamin-A-rich f/v	Other f/v
Availability	**Rural (base Urban)**	-0.02	**0.12*****	**-0.24*****	-0.05	**-0.27*****	0.05	**-0.08****
	CI	[-0.14 - 0.10]	[0.05 - 0.20]	[-0.30 - -0.17]	[-0.12 - 0.01]	[-0.35 - -0.19]	[-0.01 - 0.12]	[-0.15 - -0.01]
Household Resources	***HH Wealth Quintile (base lowest quintile)***							
	HH Decile 2	0.05	0.03	0.06*	**0.10*****	**0.15*****	0.01	**0.11*****
	CI	[-0.06 - 0.16]	[-0.04 - 0.10]	[-0.01 - 0.14]	[0.04 - 0.17]	[0.06 - 0.24]	[-0.05 - 0.08]	[0.04 - 0.18]
	HH Decile 3	-0.03	**0.08****	**0.28*****	**0.20*****	**0.19*****	0.03	**0.26*****
	CI	[-0.14 - 0.08]	[0.01 - 0.16]	[0.21 - 0.36]	[0.13 - 0.27]	[0.10 - 0.28]	[-0.04 - 0.10]	[0.18 - 0.33]
	HH Decile 4	0.04	-0.03	**0.63*****	**0.25*****	**0.41*****	**-0.08****	**0.38*****
	CI	[-0.08 - 0.17]	[-0.11 - 0.05]	[0.54 - 0.71]	[0.17 - 0.32]	[0.31 - 0.51]	[-0.16 - -0.00]	[0.30 - 0.47]
	HH Decile 5	0.02	-0.06	**1.29*****	**0.27*****	**0.60*****	**-0.14*****	**0.54*****
	CI	[-0.14 - 0.18]	[-0.16 - 0.04]	[1.19 - 1.39]	[0.18 - 0.37]	[0.49 - 0.71]	[-0.23 - -0.05]	[0.44 - 0.63]
Education and Awareness	**Age of child in months**	**0.04*****	**0.04*****	-0.00	**0.07*****	**0.03*****	**0.05*****	**0.05*****
	CI	[0.04 - 0.05]	[0.03 - 0.04]	[-0.01 - 0.00]	[0.07 - 0.08]	[0.03 - 0.04]	[0.04 - 0.05]	[0.04 - 0.05]
	Maternal Education (base no education)							
	Primary education	0.09*	**-0.10*****	0.03	**0.07****	**0.22*****	**0.07****	**0.14*****
	CI	[-0.01 - 0.19]	[-0.17 - -0.04]	[-0.04 - 0.09]	[0.01 - 0.13]	[0.14 - 0.30]	[0.01 - 0.13]	[0.07 - 0.21]
	Secondary education or higher	**0.20*****	**-0.08****	**0.54*****	**0.14*****	**0.32*****	**0.08****	**0.28*****
	CI	[0.07 - 0.33]	[-0.16 - -0.00]	[0.47 - 0.62]	[0.07 - 0.22]	[0.23 - 0.41]	[0.01 - 0.14]	[0.20 - 0.35]
Others	**Female Sex**	-0.03	0.01	0.02	-0.01	-0.01	-0.01	-0.02
	CI	[-0.10 - 0.05]	[-0.04 - 0.06]	[-0.02 - 0.07]	[-0.06 - 0.03]	[-0.06 - 0.05]	[-0.05 - 0.03]	[-0.07 - 0.03]
	Household Size	0.00	**0.01*****	-0.00	**-0.01****	-0.01	0.00	-0.01*
	CI	[-0.01 - 0.01]	[0.00 - 0.02]	[-0.01 - 0.00]	[-0.01 - -0.00]	[-0.01 - 0.00]	[-0.00 - 0.01]	[-0.01 - 0.00]
	Age at mother at birth in years	0.00	-0.00	0.00	-0.00	**-0.01****	**0.01*****	0.00*
	CI	[-0.00 - 0.01]	[-0.00 - 0.00]	[-0.00 - 0.00]	[-0.00 - 0.00]	[-0.01 - -0.00]	[0.00 - 0.01]	[-0.00 - 0.01]
Religion & Faith	***Religion (base no religion/faith)***							
	Animism/traditional	0.19	-0.10	0.09	-0.19	-0.18	-0.06	**-0.46****
	CI	[-0.41 - 0.79]	[-0.41 - 0.22]	[-0.27 - 0.46]	[-0.50 - 0.12]	[-0.58 - 0.22]	[-0.35 - 0.22]	[-0.86 - -0.06]
	Buddhism	-0.38	0.35	0.18	-0.41*	-0.20	0.12	0.01
	CI	[-1.60 - 0.84]	[-0.19 - 0.89]	[-0.34 - 0.70]	[-0.88 - 0.07]	[-0.71 - 0.30]	[-0.30 - 0.54]	[-0.41 - 0.43]
	Christian	-0.25*	0.12	**0.19****	-0.07	0.09	-0.03	**0.18****
	CI	[-0.54 - 0.04]	[-0.04 - 0.28]	[0.02 - 0.36]	[-0.23 - 0.09]	[-0.10 - 0.28]	[-0.19 - 0.12]	[0.02 - 0.34]
	Hindu	0.21	-0.02	**0.89*****	**-0.67*****	**-0.33****	0.21	0.25*
	CI	[-0.25 - 0.67]	[-0.34 - 0.31]	[0.62 - 1.17]	[-0.95 - -0.40]	[-0.62 - -0.05]	[-0.07 - 0.49]	[-0.01 - 0.50]
	Islam	-0.05	-0.02	**0.65*****	-0.13	0.19*	-0.02	0.10
	CI	[-0.36 - 0.26]	[-0.19 - 0.16]	[0.46 - 0.84]	[-0.31 - 0.05]	[-0.02 - 0.40]	[-0.19 - 0.15]	[-0.08 - 0.27]
	Sikh	0.23	-0.43*	**1.50*****	**-2.92*****	**-1.44*****	-0.20	**0.38****
	CI	[-0.35 - 0.81]	[-0.86 - 0.00]	[1.11 - 1.90]	[-3.72 - -2.13]	[-1.91 - -0.98]	[-0.51 - 0.12]	[0.08 - 0.69]
	Jewish	-0.34	0.16	**0.56****	-0.19	-0.15	0.08	**0.41****
	CI	[-1.12 - 0.44]	[-0.20 - 0.53]	[0.11 - 1.01]	[-0.53 - 0.15]	[-0.61 - 0.31]	[-0.27 - 0.43]	[0.08 - 0.75]
	Other	-0.05	0.08	-0.14	-0.07	**0.29****	0.15	**0.26****
	CI	[-0.44 - 0.34]	[-0.15 - 0.31]	[-0.43 - 0.15]	[-0.29 - 0.15]	[0.02 - 0.56]	[-0.10 - 0.40]	[0.03 - 0.50]

Equal country weights, ∗P < 0.05, ∗∗P < 0.01, ∗∗∗P < 0.001; 95% CI in brackets, n= 129,017 observations from 41 countries

Supplement Table IV.3: Regression results child and household characteristics on food group consumption level for all children in sample

	FGs	Grains	Legumes, nuts	Dairy	Flesh foods	Eggs	Vitamin-A-rich f/v	Other f/v
Availability	**Rural (base Urban)**	**-0.05****	**0.06****	**-0.26*****	**-0.12*****	**-0.21*****	-0.02	**-0.10*****
	CI	[-0.11 - -0.00]	[0.01 - 0.11]	[-0.30 - -0.21]	[-0.16 - -0.07]	[-0.27 - -0.16]	[-0.06 - 0.03]	[-0.15 - -0.05]
Household Resources	***HH Wealth Quintile (base lowest quintile)***							
	HH Decile 2	**0.08*****	**0.07****	**0.09*****	**0.14*****	**0.14*****	**0.07*****	**0.17*****
	CI	[0.03 - 0.13]	[0.02 - 0.12]	[0.04 - 0.15]	[0.09 - 0.19]	[0.08 - 0.20]	[0.02 - 0.11]	[0.11 - 0.22]
	HH Decile 3	**0.12*****	**0.17*****	**0.29*****	**0.29*****	**0.23*****	**0.17*****	**0.34*****
	CI	[0.07 - 0.18]	[0.11 - 0.23]	[0.24 - 0.35]	[0.24 - 0.34]	[0.16 - 0.29]	[0.12 - 0.22]	[0.28 - 0.40]
	HH Decile 4	**0.16*****	**0.15*****	**0.57*****	**0.33*****	**0.37*****	**0.16*****	**0.49*****
	CI	[0.10 - 0.22]	[0.09 - 0.21]	[0.51 - 0.63]	[0.27 - 0.38]	[0.30 - 0.44]	[0.11 - 0.22]	[0.43 - 0.56]
	HH Decile 5	**0.34*****	**0.23*****	**1.18*****	**0.48*****	**0.60*****	**0.27*****	**0.70*****
	CI	[0.27 - 0.42]	[0.16 - 0.31]	[1.10 - 1.25]	[0.41 - 0.55]	[0.52 - 0.68]	[0.20 - 0.33]	[0.63 - 0.78]
Education and Awareness	**Age of child in months**	**0.13*****	**0.07*****	**0.04*****	**0.11*****	**0.07*****	**0.09*****	**0.08*****
	CI	[0.13 - 0.13]	[0.07 - 0.07]	[0.03 - 0.04]	[0.11 - 0.11]	[0.07 - 0.08]	[0.08 - 0.09]	[0.07 - 0.08]
	Maternal Education (base no education)							
	Primary education	**0.15*****	**0.07*****	**0.07*****	**0.18*****	**0.33*****	**0.12*****	**0.25*****
	CI	[0.10 - 0.20]	[0.02 - 0.12]	[0.02 - 0.12]	[0.14 - 0.23]	[0.27 - 0.39]	[0.07 - 0.16]	[0.20 - 0.31]
	Secondary education or higher	**0.33*****	**0.15*****	**0.56*****	**0.37*****	**0.51*****	**0.25*****	**0.48*****
	CI	[0.27 - 0.39]	[0.09 - 0.22]	[0.50 - 0.61]	[0.32 - 0.43]	[0.45 - 0.58]	[0.20 - 0.30]	[0.42 - 0.54]
Others	**Female Sex**	-0.01	-0.02	0.01	-0.03	-0.04*	**-0.03****	-0.02
	CI	[-0.04 - 0.03]	[-0.06 - 0.01]	[-0.02 - 0.04]	[-0.06 - 0.01]	[-0.07 - 0.00]	[-0.06 - -0.00]	[-0.05 - 0.02]
	Household Size	0.00	**0.01****	-0.00	-0.00	-0.01*	-0.00	**-0.01*****
	CI	[-0.00 - 0.01]	[0.00 - 0.01]	[-0.01 - 0.00]	[-0.01 - 0.00]	[-0.01 - 0.00]	[-0.00 - 0.00]	[-0.01 - -0.00]
	Age at mother at birth in years	0.00	0.00*	0.00	-0.00	-0.00*	**0.01*****	**0.00****
	CI	[-0.00 - 0.00]	[-0.00 - 0.01]	[-0.00 - 0.00]	[-0.00 - 0.00]	[-0.01 - 0.00]	[0.00 - 0.01]	[0.00 - 0.01]

Equal country weights, ∗P < 0.05, ∗∗P < 0.01, ∗∗∗P < 0.001; 95% CI in brackets, n= 263,003 observations from 55 countries

Chapter V

The scope of economic growth for reducing early childhood malnutrition: cross-sectional analysis of 239 DHS surveys from 58 LMICs based on UNICEF's Conceptual Framework of the Determinants of Maternal and Child Nutrition

With: Nicolas Büttner, Jan-Walter De Neve, Sebastian Vollmer, Kenneth Harttgen

Abstract

Economic growth may reduce malnutrition through improvements in several underlying and immediate determinants which potentially contribute to malnutrition, but the empirical evidence is mixed. In this paper, we analyzed the relationship between per-head gross domestic product (GDP), malnutrition, and potential contributing factors based on UNICEF's Conceptual Framework on the Determinants of Maternal and Child Nutrition. We included children aged 0–35 months from 239 Demographic and Health Surveys covering 58 LMICs. We considered stunting, wasting, underweight, overweight, obesity, and dietary diversity failure, as well as a wide range of contributing factors, defined as underlying and immediate determinants that affect child malnutrition. We used multilevel logistic regression models to estimate the associations between: (i) per-head GDP and malnutrition, (ii) contributing factors and malnutrition, and (iii) per-head GDP and contributing factors. Overall, 27·33% of children were stunted, 25·70% were underweight, 11·15% were wasted, 3·77% had overweight, 1·08% had obesity, and 79·82% had dietary diversity failure. In the pooled sample, per-head GDP was weakly and ambiguously associated with malnutrition outcomes. Although we found strong associations between many contributing factors and most outcomes for malnutrition, we generally identify weak and ambiguous associations between per-head GDP and contributing factors. We conclude that economic growth alone does not necessarily affect child malnutrition and several contributing factors. Economic growth may need to be accompanied by more targeted investments directed toward women's health, including access to reproductive health services, maternal educational attainment, and access to improved sanitation in low-resource settings.

V.1 Introduction

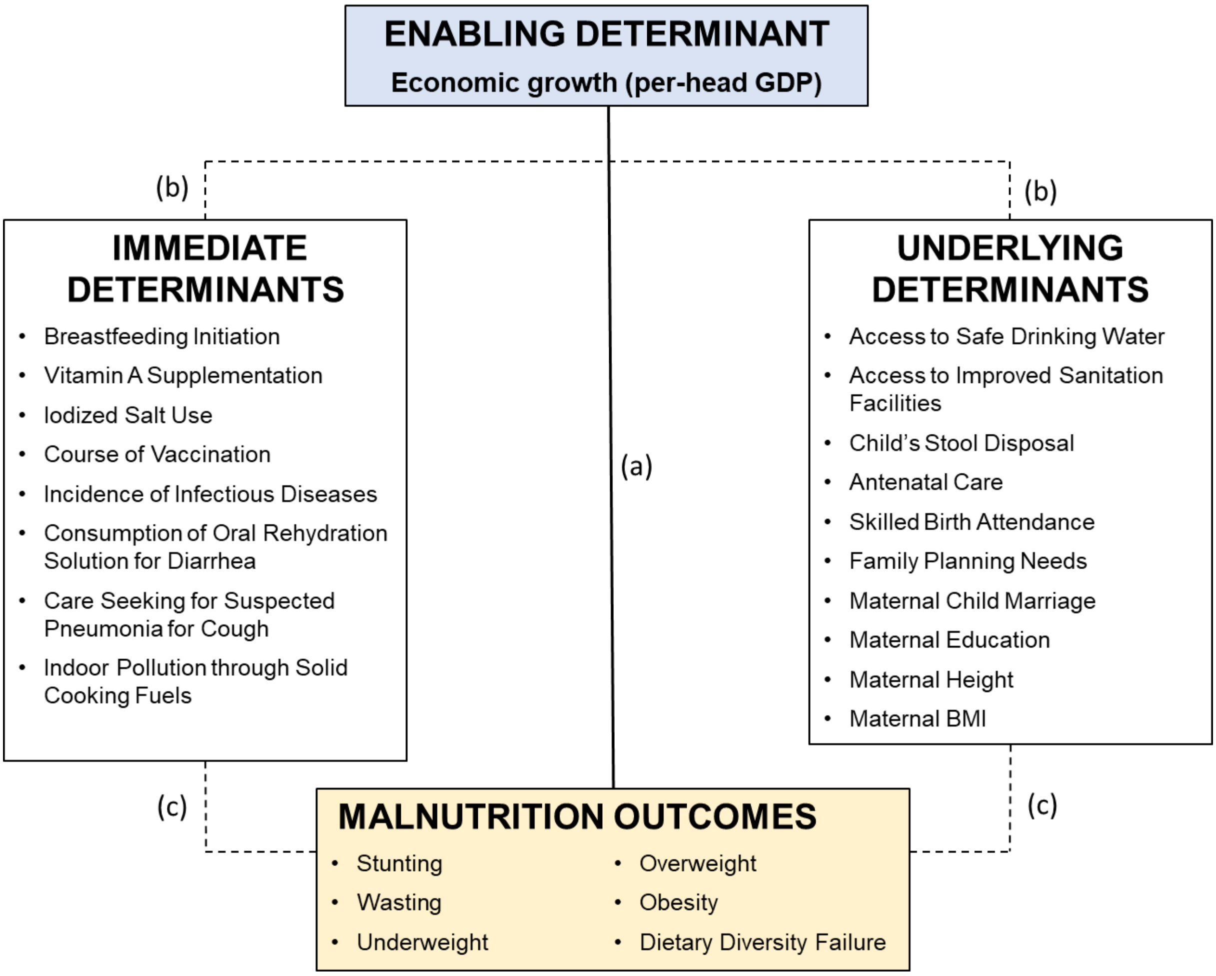
Economic growth has been the focus of development policy for many national governments.[1] The trickle-down theories of macroeconomics are manifested in healthcare policies whose proponents argue that economic growth will automatically lead to a better quality of life and better health, including lesser early childhood malnutrition.[2,3,4] Yet, recent evidence suggests that economic growth has only a weak direct association with reductions in early childhood stunting, wasting, and underweight.[5] At the same time, the Sustainable Development Goals (SDGs) emphasize ending all forms of malnutrition by 2030, including achieving by 2025 the internationally agreed targets on stunting and wasting in children under five. In addition, there has been an alarming increase in childhood overweight and obesity in recent years, especially in emerging countries.[6] This highlights the need for policymakers to better understand the factors that contribute to early childhood malnutrition, including overweight, as well as the conditions that influence these factors to channel policy efforts in the right direction and improve children's well-being.

For this purpose, UNICEF developed a conceptual framework of malnutrition in 1990 as part of their "Strategy for Improved Nutrition of Children and Women in Developing Countries".[7] Since then, this framework has been continuously revised to "reflect advances in knowledge and priorities in child health and nutrition".[8] In 2020, UNICED developed their new 'Conceptual Framework on the Determinants of Maternal and Child Nutrition', which builds on their initial 1990 framework but acknowledges the increasing triple burden of malnutrition, including overweight and micronutrient deficiencies, and further highlights the role of diets and care as immediate determinants of child nutrition.[9] It describes the role of enabling determinants, underlying determinants, and immediate determinants in children's and mothers' nutritional outcomes. Enabling determinants include political, financial, social, cultural, and environmental conditions and influence children's health through immediate determinants and underlying determinants. Immediate determinants of malnutrition are more directly related to child malnutrition, like diets and care, while underlying determinants of malnutrition refer to family and community characteristics influencing a child's well-being more indirectly (such as maternal educational attainment) (Figure A1).

To our knowledge, no study has empirically tested this framework in a comprehensive way. Few studies have analyzed the multilevel association between aggregate economic growth and children's individual risk of being malnourished. No evidence for such an association was found for India[10], while for Egypt, a significant negative relationship was found.[11] Two studies used large samples of pooled Demographic and Health Surveys (DHS), and both found a small, inverse association between childhood stunting, underweight, and wasting with economic growth.[5,12] One study found a large, inverse association between childhood stunting and economic growth based on pooled DHS from 20 African countries.[13] Empirical studies that investigate multiple household-level contributing factors of childhood malnutrition are also scarce. One recent cross-country study considered nine direct and 17 indirect factors but only analyzed stunting, underweight, and wasting as malnutrition indicators (omitting overweight, obesity, and dietary diversity failure).[14] Other studies did similar analyses for a specific country, like India[15] and Kenya[16]. A systematic review identified maternal education, household income, maternal nutrition, and access to sanitation as the most important contributing factors to childhood malnutrition.[17]

In this study, we aim to contribute to our understanding of the links between economic growth, childhood malnutrition, and several potential contributing factors in low- and middle-income countries (LMICs). Combining individual-level data from 239 DHS from 58 LMICs, we first investigate the multilevel association between countries' per-head gross-domestic-product (GDP) and children's risk of being malnourished. We test whether the overall mechanism from economic growth to reductions in child malnutrition holds. We build on prior work by Vollmer and Colleagues[5] but use substantially more surveys and countries. In addition, we do not only focus on undernutrition in the form of stunting, underweight, and wasting but also consider overweight and obesity, as well as dietary diversity failure, consistent with the 2020 UNICEF Conceptual Framework on Maternal and Child Nutrition. Second, we analyze the associations of household-level contributing factors with malnutrition to test which contributing factors may provide the biggest scope for economic growth to reduce malnutrition. Lastly, we investigate the relationship between per-head GDP and contributing factors to test whether economic growth can reduce child malnutrition via these contributing factors of malnutrition. If economic growth is not related to contributing factors, however, malnutrition may need to be addressed in different ways through more targeted investments in LMICs (e.g., increased access to health services).

Figure V.1: Conceptual framework for economic growth and child malnutrition



Most prior studies assess the indirect relationship between economic growth and undernutrition, which can be interpreted as the total effect of economic growth on undernutrition (a). In the current study, we determine the direct relationship between economic growth and contributing factors (b) and the direct relationship between contributing factors and undernutrition (c). The effects (b) and (c) can be interpreted as the partial effects of economic growth on undernutrition. Additionally, we assess overnutrition and dietary diversity failure as further dimensions of malnutrition. Abbreviations: GDP=gross domestic product. Framework adapted from the 2020 UNICEF Conceptual Framework on Maternal and Child Nutrition.[9]

V.2 Methods

Data sources

Malnutrition

Our data came primarily from the DHS, which have been conducted by ICF International in over 90 low- and middle-income countries. The cross-sectional surveys use a multistage stratified sampling design and are nationally representative. They collect data regarding the health and welfare of women of reproductive age (typically aged 15–49 years), their children (born within the past five years of data collection), their partner, and their household. A key advantage of the DHS is the availability of comparable data for multiple countries and consistent quality of reporting and data over time. Additional details on the DHS surveys are available elsewhere.[18] We restricted our sample to surveys conducted between Jan 1, 1990, and Dec 31, 2020. Our sample was further restricted to countries where at least two surveys with all relevant data were available. For each country year, we extracted data from the Individual Recode files of the DHS.

Economic growth

Data on per-head GDP were from the Penn World Tables 10.0, which provide national aggregate data for real per-head GDP per year.[19] GDP was adjusted for purchasing power parity to facilitate comparisons across countries. The aggregate GDP data by country and survey year from the Penn World Tables was merged with the individual-level DHS data based on country and year.

Study population

We focused on children aged 0–35 months because in most DHS anthropometric measurements are only available among children in this age group. We included all children born in a household surveyed by the DHS and for whom complete data on malnutrition and contributing factors were available. This yielded a maximum sample size of 1,138,568 children from 239 DHS surveys in 58 countries with data on both per-head GDP and our outcomes (Supplement Table A1).

Exposure

Our exposure was per-head GDP aggregated at the country-year level. Per-head GDP was measured in logarithmic units to capture nonlinear associations with the outcomes of interest.

GDP was defined, so that odds ratios in logistic regression models correspond to a 5% increase in per-head GDP.

Outcomes

Early childhood malnutrition

Our primary outcome was individual-level childhood malnutrition, following the WHO 2006 Child Growth Standards.[20] We considered binary indicators of stunting (=1 if height-for-age z-score < –2), wasting (=1 if weight-for-height z-score < –2), and underweight (=1 if weight-for-age z-score < –2). Overnutrition was measured by binary indicators of overweight (=1 if weight-for-height z-score > 2) and obesity (=1 if weight-for-height z-score > 3). For stunting, z-scores were calculated as the child's height minus the median height for that child's age and sex in the WHO reference population, divided by the standard deviation of this group in the reference population.[21] Z-scores for the other outcomes were calculated analogously. Biologically implausible values (defined by the WHO as, for example, a z-score less than −6 or greater than 6 for height) were excluded.[20] We also analyzed dietary diversity failure since there is evidence that anthropometric measures alone do not sufficiently capture malnutrition and should thus be complemented with dietary-based measures.[22] It was measured as a binary indicator based on a score ranging from zero to eight, with one point assigned for consuming grains, roots and tubers, legumes and nuts, dairy products, flesh foods, eggs, vitamin-A-rich fruits, and vegetables in the last 24 hours before the interview. Scores lower than five indicated dietary diversity failure.

Potential contributing factors of malnutrition

Our secondary outcomes were potential contributing factors of malnutrition (Supplement Table A2). The allocation of contributing factors into underlying determinants and immediate determinants was not always straightforward, but we were guided conceptually by the 2020 UNICEF Conceptual Framework on Maternal and Child Nutrition and also closely followed existing empirical studies.[14] First, as *underlying determinants*, we considered the following outcomes: No Access to Safe Drinking Water, No Access to Improved Sanitation Facilities, Unsafe Practices for Child's Stool Disposal, Inadequate Antenatal Care, No Skilled Birth Attendant, Unsatisfied Family Planning Needs, Maternal Child Marriage, No Maternal Education, Low Maternal Height, and Low/High Maternal BMI. Second, as *immediate determinants,* we considered the following outcomes: Delayed Breastfeeding Initiation, No Vitamin A Supplementation, No Iodized Salt Use, Incomplete Course of Vaccination, Incidence of Infectious Diseases, No Consumption of Oral Rehydration Solution despite Diarrhea, No Care Seeking for Suspected Pneumonia despite Cough, and High Indoor Pollution through Solid Cooking Fuels. We hypothesized that these factors would be positively correlated with malnutrition, and in particular undernutrition. All outcomes were coded as binary variables with the "better" category serving as the reference category.

Control variables

We constructed two sets of control variables. Household control variables included the household's wealth quintile (with five being richest), size, and location (urban/rural). Child and mother control variables included the child's sex, age, birth order, and the mother's age at birth. Additionally, we added indicators for country to take into account all observed and unobserved country-level factors (or above). We also controlled for survey-year to control for period effects and potential differences in measurement across survey years.

Statistical analysis

The analysis comprised three parts. *First*, we used multilevel logistic regression models to obtain odds ratios and 95% confidence intervals (CIs) for the relationship between per-head GDP and our outcomes for child malnutrition, including undernutrition, overnutrition, and dietary diversity failure (displayed as (a) in Figure 1). Although prior research has indicated associations between economic growth and undernutrition[5,10–13], less is known about the relationship between economic growth and overnutrition and dietary diversity failure. *Second*, we regressed our outcomes for child malnutrition on potential contributing factors of child malnutrition, including underlying determinants and immediate determinants (displayed as (c) in Figure 1). This analysis allowed us to assess which contributing factors may provide the biggest scope for economic growth to reduce malnutrition. For example, if we identify meaningful associations of household-level contributing factors with malnutrition (such as maternal educational attainment), this contributing factor may provide a larger scope for economic growth to reduce malnutrition compared to other hypothesized contributing factors (such as access to health services). We estimated odds ratios using separate regression models for each malnutrition outcome but including all potential contributing factors as covariates. Here, we only used data from the latest available survey of each country and only analyzed the youngest child of the mother as the associations between contributing factors and malnutrition have likely changed over the study period. *Third*, we investigated the relationship between per-head GDP and all potential contributing factors of malnutrition to test whether economic growth can reduce child malnutrition via these factors. To do so, we regressed each of these contributing factors of child malnutrition on per-head GDP (displayed as (b) in Figure 1). Our aim was to empirically test the 2020 UNICEF Conceptual Framework on Maternal and Child Nutrition and identify contributing factors that may provide the largest scope for economic growth to reduce malnutrition in LMICs.

In all regressions with malnutrition as outcomes, household control variables (wealth quintile, size, and location) and child and mother control variables (child's sex, age, birth order, and maternal age) were included. In all regressions with contributing factors to malnutrition as outcomes, household control variables (wealth quintile, size, and location) were included. We clustered standard errors by primary sampling unit (PSU) and controlled for country-fixed effects in all models. When using multiple DHS per country, i.e., whenever per-head GDP was the main regressor, we also controlled for survey-year fixed effects. Sample weights were used in descriptive statistics but not in regression analyses. All results are displayed as odds ratios and associations with a p-value of less than 0·05 were regarded as significant.

Sensitivity analyses

We conducted several sensitivity analyses based on a linear probability model (instead of logistic regression models). First, we reweighted the observations with the population size of the country, using data from the UN population prospects. Second, we trimmed the sample to exclude extreme observations with regard to childhood malnutrition (1st, 2nd, 3rd, 98th, 99th, and 100th percentile). Third, we used instrumental variable regressions with the investment share of GDP five years ago as an instrument for log per-head GDP to address two potential statistical problems: measurement error in GDP which could bias the results downwards; and endogeneity of GDP, which could bias the findings because of either reverse causality or omitted variable bias.

Data availability and ethics clearance

This was a complete case analysis. All analyses were conducted in Stata v17. As DHS surveys are publicly available anonymized datasets, this study was exempt from institutional ethical review based on national and institutional policies.

V.3 Results

Sample description

In the pooled sample, 27·33% (95% CI 27·24%–27·42%) of children were stunted, 25·70% (25·62%–25·79%) were underweight, 11·15% (11·09%–11·22%) were wasted, 3·77% (3·73%–3·81%) had overweight, 1·08% (1·06%–1·10%) had obesity, and 79·82% (79·71%–79·93%) had dietary diversity failure.

Table 1 provides summary statistics for all variables used in our analysis, aggregated at the country level, and using the latest DHS for each country. There was substantial variation in per-head GDP and malnutrition rates across countries and survey years. Per-head GDP ranged from $785 in Burundi to $ 23,118 in Turkey. Stunting ranged from 6·1% in Jordan to 42·3% in Burundi; wasting ranged from 0·9% in Peru to 22·3% in Timor-Leste; underweight ranged from 2·2% in Albania to 43·3% in Timor-Leste; overweight ranged from 1·0% in Burundi to 12·6% in Morocco; obesity ranged from 0·1% in Nepal to 4·2% in Morocco; and dietary failure ranged from 41·9% in Peru to 93·9% in Liberia.

Table V.1: Summary statistics

Variables	# N	# C	Mean	SD	Min	Max
Indicators of Malnutrition						
Stunting	320,502	57	21·1%	8·8%	6·1%	42·3%
Wasting	320,736	57	6·9%	5·1%	0·9%	22·3%
Underweight	320,223	57	18·2%	10·9%	2·2%	43·3%
Overweight	320,736	57	4·2%	2·8%	1·0%	12·6%
Obesity	320,736	57	1·2%	0·9%	0·1%	4·2%
Dietary Diversity Failure	220,230	36	79·3%	11·8%	41·9%	93·9%
Immediate Determinants						
Delayed Breastfeeding Initiation	335,927	55	42·3%	16·8%	13·9%	79·0%
No Vitamin A Supplementation	352,822	45	48·0%	16·7%	9·4%	87·8%
No Iodized Salt Use	203,911	16	21·1%	23·5%	4·4%	93·5%
Incomplete Course of Vaccination	391,930	56	55·3%	14·6%	29·4%	100·0%

Incidence of Infectious Diseases	365,718	57	51·7%	24·2%	12·4%	100·0%
No Consumption of Oral Rehydration Solution despite Diarrhea	391,259	55	10·7%	5·5%	1·2%	26·9%
No care Seeking for Suspected Pneumonia despite Cough	377,784	56	8·2%	5·5%	1·3%	29·7%
High Indoor Pollution through Solid Cooking Fuels	335,950	47	70·8%	33·2%	0·0%	99·9%
Underlying Determinants						
No access to Safe Drinking Water	369,172	57	23·2%	15·7%	1·1%	61·1%
No Access to Improved Sanitation Facilities	365,187	57	41·0%	25·0%	0·0%	88·6%
Unsafe Practices for Child's Stool Disposal	269,374	41	50·9%	21·1%	9·6%	84·6%
Inadequate Antenatal Care	338,202	57	34·1%	20·0%	2·3%	74·8%
No Skilled Birth Attendant	400,643	58	26·8%	21·5%	0·0%	87·0%
Unsatisfied Family Planning Needs	224,700	56	42·8%	20·7%	2·4%	84·4%
Maternal Child Marriage	383,110	57	40·0%	17·3%	8·1%	80·2%
No Maternal Education	380,505	58	26·4%	23·8%	0·0%	85·3%
Low Maternal Height	325,219	56	3·4%	5·0%	0·1%	28·9%
Low Maternal BMI	301,183	56	8·9%	6·4%	0·4%	28·9%
Per-head GDP						
Per-head GDP in PPP	381,781	58	5,195·06	4,723·97	785·07	23,118·23
5-year lagged per-head GDP in PPP	381,781	58	5,117·01	4,657·50	800·23	21,926·87
Control Variables						
Female	381,781	58	49·3%	1·00%	46·2%	51·8%
Child Age	381,781	58	17·00	0·48	15·95	18·19
Birth Order	379,931	58	1·09	0·05	1·00	1·17
Maternal Age at Birth	381,781	58	26·89	1·16	23·55	29·92
Urban	381,781	58	35·9%	14·7%	9·1%	78·8%
Household Size	381,781	58	6·92	1·88	5·11	16·03

#N=number of observations. #C=number of countries. SD=standard deviation. Min=Minimum. Max=Maximum. BMI=body mass index (calculated as weight in kilograms divided by height in meters squared). GDP=gross domestic product. PPP=purchasing power parity. All statistics are based on the latest available DHS per country.

Association between economic growth and malnutrition

Table 2 shows odds ratios for childhood malnutrition associated with the log of per-head GDP, using separate multilevel logistic regressions with binary malnutrition indicators as outcomes, adjusted for household and child/mother covariates, survey-year fixed effects, country fixed effects, and clustering. Odds ratios correspond to a 5% increase in per-head GDP. Supplement Figure A1 additionally presents cross-sectional ecological associations between countries' per-head GDP and malnutrition.

Table V.2: Adjusted odds ratios for childhood malnutrition associated with the log of per-head GDP

	Malnutrition					
	Undernutrition			Overnutrition		Dietary Diversity Failure
Log of per-head GDP	Stunting	Wasting	Underweight	Overweight	Obesity	
OR	0·994	1·007	1·000	0·981	0·976	1·025
95% CI	[0·992–0·996]	[1·003–1·010]	[0·998–1·002]	[0·979–0·984]	[0·973–0·980]	[1·014–1·039]
p-value	<0·001	<0·001	0·734	<0·001	<0·001	<0·001
N	899,531	900,246	896,593	900,246	900,246	536,649
Countries	57	57	57	57	57	36
Years	1990–2020	1990–2020	1990–2020	1990–2020	1990–2020	2005–2020

Data for the per-head gross domestic product (GDP) were merged with Demographic and Health Survey data by survey year. SEs are clustered at the PSU level. Odds ratios (ORs) for the log of per-head GDP represent the difference in odds associated with a 5% increase in per-head GDP. All specifications include country and survey-year fixed effects as well as household and child/mother control variables. All ORs are rounded to three decimal places; thus, an OR of 1·000 in the CI does not necessarily imply that the value 1 is included in the CI.

Per-head GDP was significantly and negatively associated with stunting and positively with wasting, but for both only by a very small magnitude. A 5% increase in per-head GDP was associated with a 0·6% decrease in the odds of being stunted (p<0·001) and a 0·7% increase in the odds of being wasted (p<0·001). Per-head GDP was not significantly associated with underweight. These results for undernutrition are broadly in line with those from Vollmer and colleagues[5] and challenge the assumption that economic growth automatically translates into improvements in child undernutrition. In contrast, significant and moderately sized associations were found for overnutrition. Specifically, a 5% increase in per-head GDP was associated with a 1·9% decrease in the odds of being overweight (p<0·001) and a 2·4% decrease in the odds of being obese (p<0·001). Similarly, a 5% increase in per-head GDP was associated with a 2·5% increase in the odds of experiencing dietary diversity failure (p<0·001). This positive association might be driven by the increasing availability of (ultra-)processed foods as countries become richer.[23] Given the reduced sample size with data on dietary diversity failure and the focus on surveys from 2005 onwards, these results might only mirror the more recent relationship between economic growth and dietary diversity failure. Except for wasting, the results were robust to using linear probability models, to weighting observations by countries' population size, and to excluding outliers. Only overweight and obesity were robust to the IV-specification where the log of per-head GDP was instrumented with the investment share of GDP five years ago (Supplement Table A3).

Association between contributing factors and malnutrition

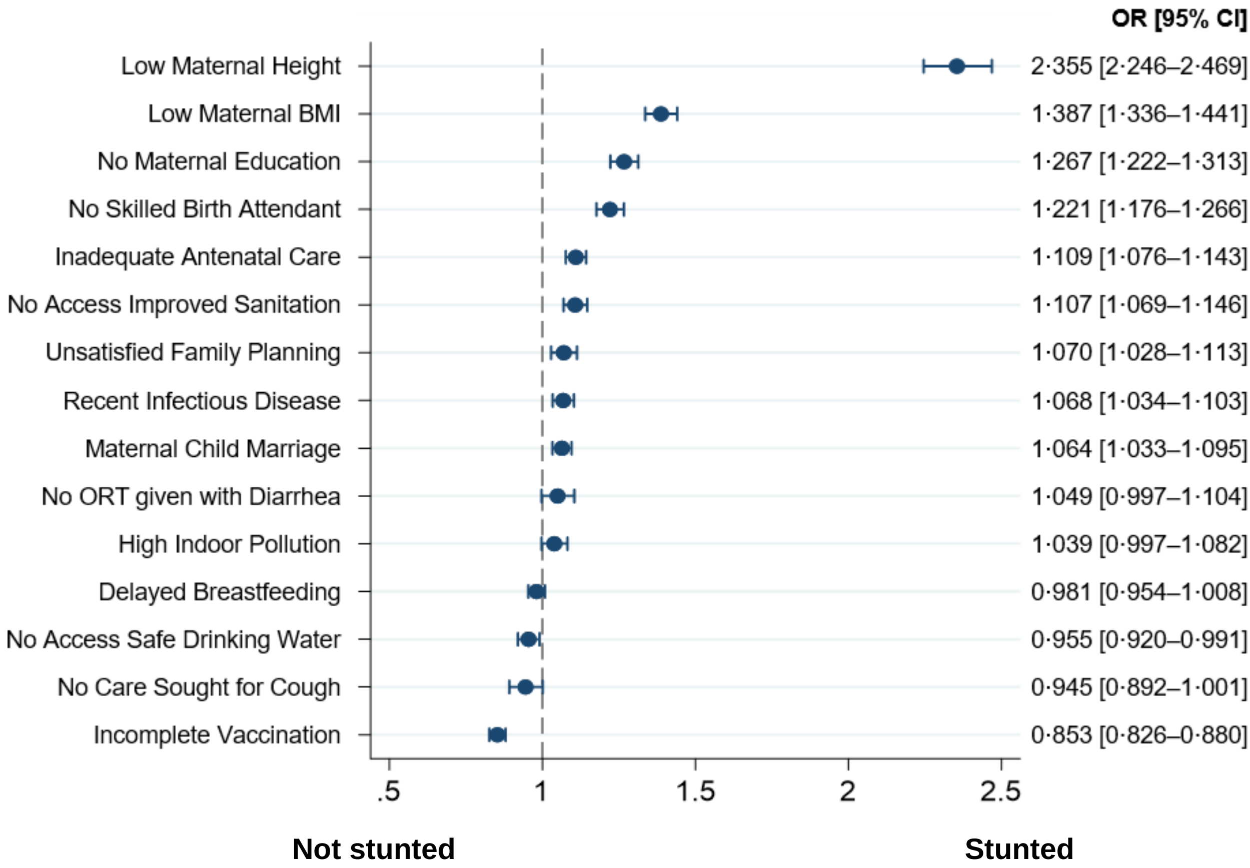
Next, we explored the association of contributing factors of malnutrition (underlying determinants and immediate determinants) with malnutrition through child-level logistic regressions, again with various malnutrition indicators as outcome variables, but now with the binary malnutrition determinants as regressors. We here show the results for one indicator per category, i.e., stunting for undernutrition, overweight for overnutrition, and dietary diversity failure. The full results are shown in the Appendix (Supplement Figure A2). To maximize sample size, the main specification did not include the covariates Unsafe Practices for Child's Stool Disposal, No Vitamin A Supplementation, and No Iodized Salt Use. The results from regressions including these covariates are also shown in the Appendix (Supplement Figure A3).

Potential contributing factors and undernutrition

Figure 2 shows the odds ratios for stunting associated with 15 binary determinants of malnutrition (see Supplement Figure A2 in Appendix for results for underweight and wasting). The theoretical framework shown in Figure 1 suggests a positive association between malnutrition and these covariates. Indeed, nine out of 15 analyzed covariates have positive and significant odds ratios. With an odds ratio (OR) of 2·36 (95% CI 2·25–2·47), Low Maternal Height shows the strongest association, followed by Low Maternal BMI (1·39, 1·34–1·44), No Maternal Education, No Skilled Birth Attendant, Inadequate Antenatal Care, and No Access to Improved Sanitation Facilities (OR 1·11, 1·07–1·15). Lastly, Unsatisfied Family Planning

Needs (1·07, 1·03–1·11), Incidence of Infectious Diseases, and Maternal Child Marriage (1·06, 1·03–1·10) increase the odds of being stunted. We found no significant associations with No Consumption of Oral Rehydration Solution despite Diarrhea, High Indoor Pollution through Solid Cooking Fuels, Delayed Breastfeeding Initiation, and No care Seeking for Suspected Pneumonia despite Cough. Against our expectation, we found negative associations for No access to Safe Drinking Water (0·96, 0·92–0·99) and Incomplete Course of Vaccination (0·85, 0·83–0·88). The latter was driven by vaccinations against measles, which was more common among stunted children. For all covariates, these results were robust to using linear probability models and to excluding outliers. For all covariates except No Skilled Birth Attendant and Maternal Child Marriage, they were also robust to weighting by population size (see Supplement Table A4).

Figure V.2: Associations between contribution factors and malnutrition (stunting)



Circles represent point estimates of odds ratios associated with stunting. All specifications include country and survey-year fixed effects as well as household and child/mother control variables. Horizontal bars indicate 95% confidence intervals. BMI=body mass index (calculated as weight in kilograms divided by height in meters squared). ORT=oral rehydration therapy. N=135,310. Countries=56.

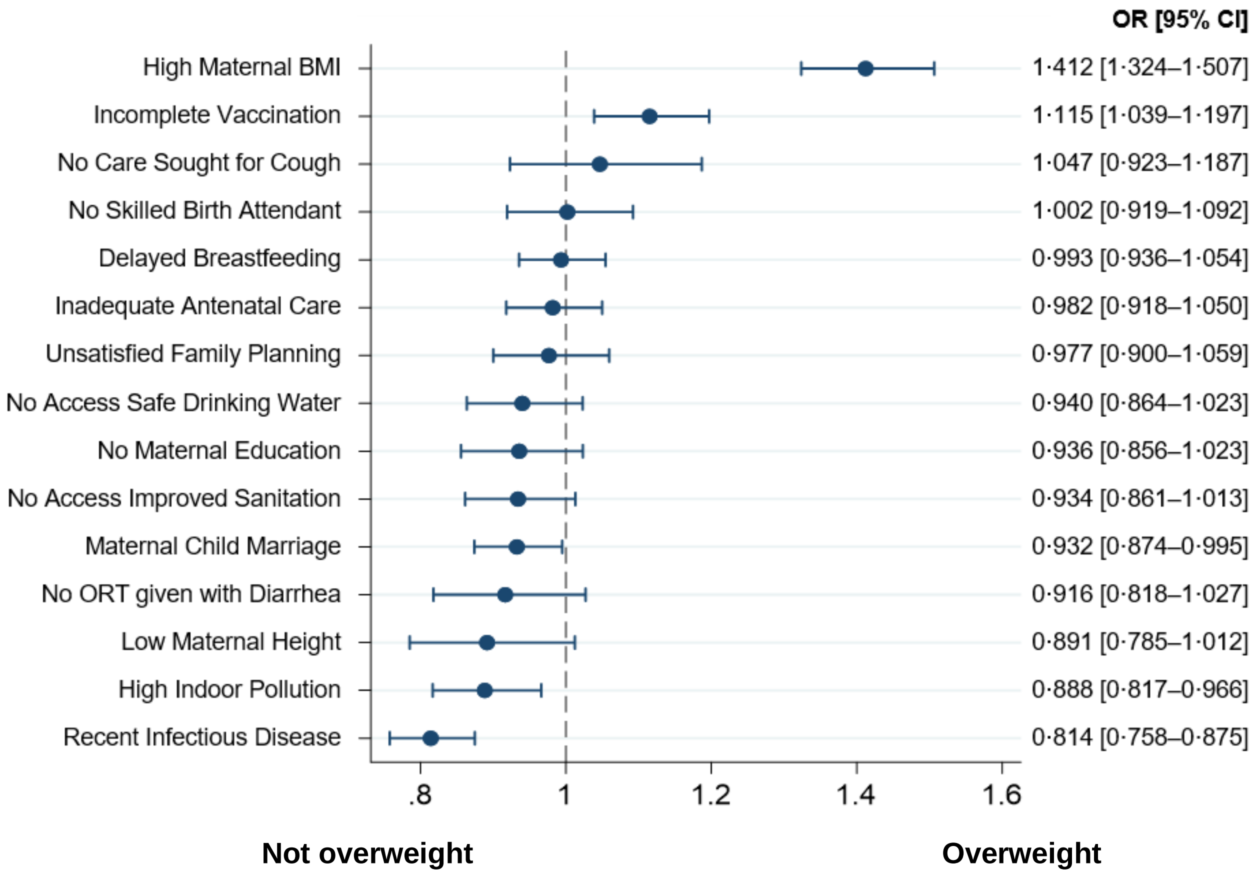
The results for underweight were very similar to those for stunting, with comparable odds ratios for most covariates (Supplement Figure A2 in Appendix). Notably, the odds ratio for Low Maternal BMI was markedly larger (1·90, 1·83–1·97), and the odds ratio for No Consumption of Oral Rehydration Solution despite Diarrhea and High Indoor Pollution through Solid Cooking Fuels became significant. The results were robust to using linear probability models, to excluding outliers (except No Consumption of Oral Rehydration Solution despite Diarrhea), and to weighting by population size (except Unsatisfied Family Planning Needs, No Consumption of Oral Rehydration Solution despite Diarrhea, and High Indoor Pollution through Solid Cooking Fuels). No access to Safe Drinking Water turned positive in all three robustness tests (Supplement Table A4).

The results for wasting were also similar, yet the odds ratios were much smaller and less precisely estimated (Supplement Figure A2 in Appendix). Positive and significant odds ratios were found for Low Maternal BMI (1·52, 1·45–1·59), Incidence of Infectious Diseases, No Maternal Education, Unsatisfied Family Planning Needs, No Access to Improved Sanitation Facilities, and No Skilled Birth Attendant (1·07, 1·01–1·12), yet the latter three were not robust to our sensitivity tests. Our results are in line with those found by Li and colleagues[14], despite some differences in the magnitudes. They confirm an important link between many of the potential contributing factors and the incidence of undernutrition, yet much stronger for stunting and underweight than for wasting. The associations were statistically significant mostly for underlying determinants and less so for immediate determinants and suggest that the biggest scope for reductions in childhood undernutrition is through improvements in mothers' health and education, reproductive health services, and, to a lesser extent, housing conditions.

Potential contributing factors and overnutrition

Figure 3 shows odds ratios for overweight associated with determinants of malnutrition. Positive and significant odds ratios were only found for High Maternal BMI (OR 1·41, 1·32–1·51), and Incomplete Course of Vaccination (OR 1·12, 1·04–1·20), while for most remaining covariates odds ratios are either insignificant or negative and of small to moderate magnitude. A similar pattern can be observed for obesity. For both measures of overnutrition, the positive associations with High Maternal BMI and Incomplete Course of Vaccination remain robust to all sensitivity tests. These results suggest that the 2020 UNICEF Conceptual Framework on Maternal and Child Nutrition is less suitable for the analysis of child overnutrition as compared to undernutrition. Leading causes of childhood overweight and obesity are factors like a high intake of energy-dense and nutrient-poor foods and beverages as well as sedentary activities, which are not captured in the framework.[24]

Figure V.3: Associations between contribution factors and malnutrition (overweight)



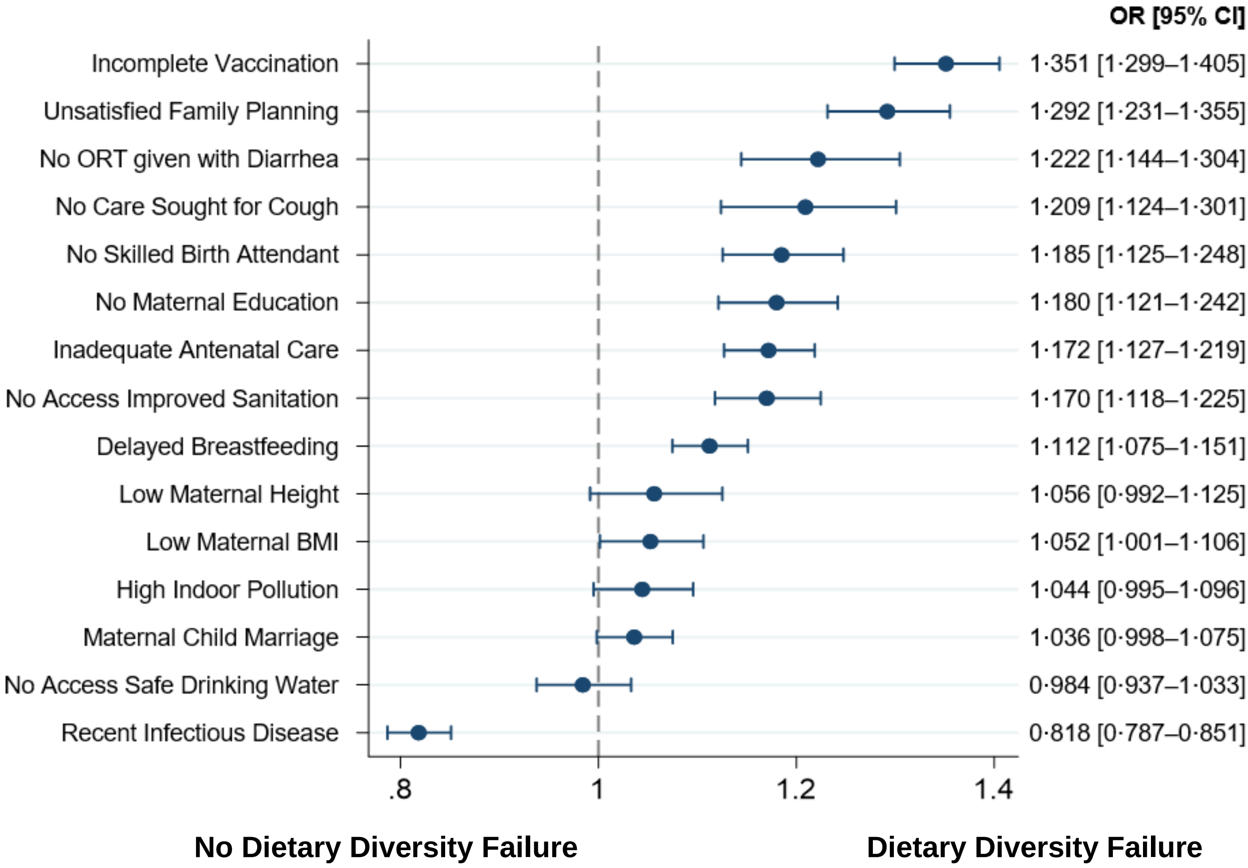
Circles represent point estimates of odds ratios associated with overweight. All specifications include country and survey-year fixed effects as well as household and child/mother control variables Horizontal bars indicate 95% confidence intervals. BMI=body mass index (calculated as weight in kilograms divided by height in meters squared). ORT=oral rehydration therapy. N=135,669. Countries=56.

Potential contributing factors and dietary diversity failure

Dietary diversity failure is positively and significantly associated with ten out of 15 covariates, most strongly with Incomplete Course of Vaccination (OR 1·35, 95% CI 1·30–1·41), followed by Unsatisfied Family Planning Needs (1·29, 1·23–1·36), No Consumption of Oral Rehydration Solution despite Diarrhea, No Care Seeking for Suspected Pneumonia despite

Cough, No Skilled Birth Attendant, No Maternal Education, Inadequate Antenatal Care, No Access to Improved Sanitation Facilities, Delayed Breastfeeding Initiation, and Low Maternal BMI (1·05, 1·00–1·11) (Figure 4). These results were robust to all sensitivity tests. Immediate determinants and underlying determinants are relatively equally represented among these covariates. Overall, health-related practices seem to be the important determinants of dietary diversity failure, yet mother's level of education and housing conditions also play a non-negligible role.

Figure V.4: Associations between contribution factors and malnutrition (dietary diversity failure)



Circles represent point estimates of odds ratios associated with dietary diversity failure. All specifications include country and survey-year fixed effects as well as household and child/mother control variables Horizontal bars indicate 95% confidence intervals. BMI=body mass index (calculated as weight in kilograms divided by height in meters squared). ORT=oral rehydration therapy. N=98,842. Countries=51.

Association between economic growth and contributing factors

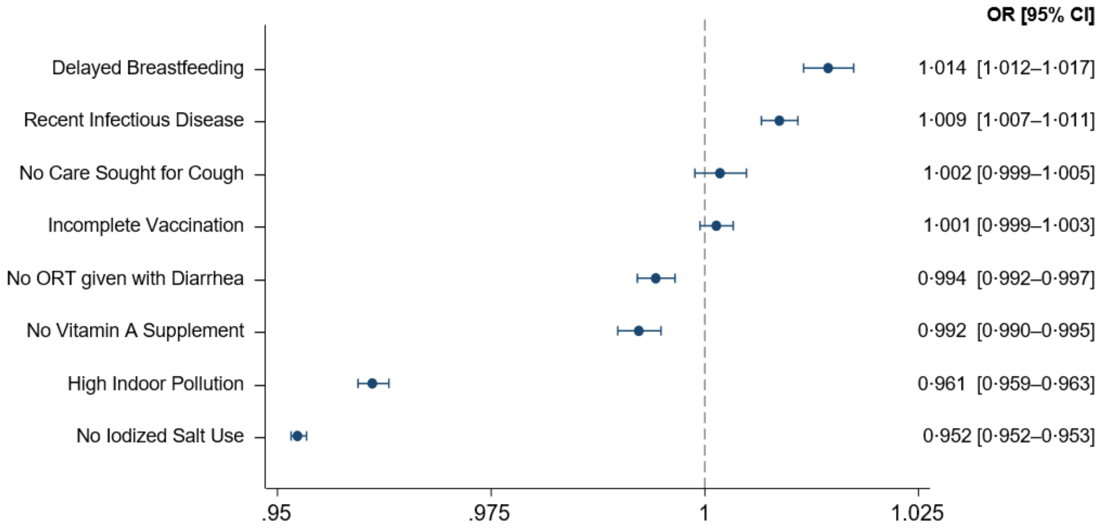
Lastly, we analyzed how the different contributing factors of malnutrition are related to economic growth. For this, multilevel logistic regressions were run, each with a contributing factor of malnutrition (binary) as an outcome and per-head GDP as the main regressor, adjusted for household covariates, survey-year fixed effects, country fixed effects, and clustering. Figure 5 show the results for (a) immediate determinants and (b) underlying determinants. Odds ratios correspond to a 5% increase in per-head GDP. The theoretical framework predicted a negative association between economic growth and determinants of malnutrition, but this was not unanimously confirmed by our analysis. Among immediate determinants, sizeable negative associations with per-head GDP were only found for No Iodized Salt Use (OR 0·952, 95% CI 0·952–0·953) and High Indoor Pollution through Solid Cooking Fuels (0·961, 0·959–0·963), which both were robust to all sensitivity tests except for IV-regressions (Supplement Table A5). Small negative associations were also found for No Vitamin A Supplementation (0·992, 0·990–0·995) and No Consumption of Oral Rehydration Solution despite Diarrhea (0·994, 0·992–0·997), the latter not being robust to excluding outliers or IV-regressions. The remaining immediate determinants were positively or insignificantly associated with per-head GDP.

We found negative and significant associations between most underlying determinants and per-head GDP. However, apart from Unsafe Practices for Child's Stool Disposal (0·968, 0·966–0·970), odds ratios were very small. No Access to Safe Drinking Water and Unsatisfied Family Planning Needs were positively associated with per-head GDP. Unsafe Practices for Child's Stool Disposal and Access to Improved Sanitation were robust to all sensitivity tests, and Inadequate Antenatal Care, Low Maternal Height, and Low Maternal BMI were robust to all except IV regressions.

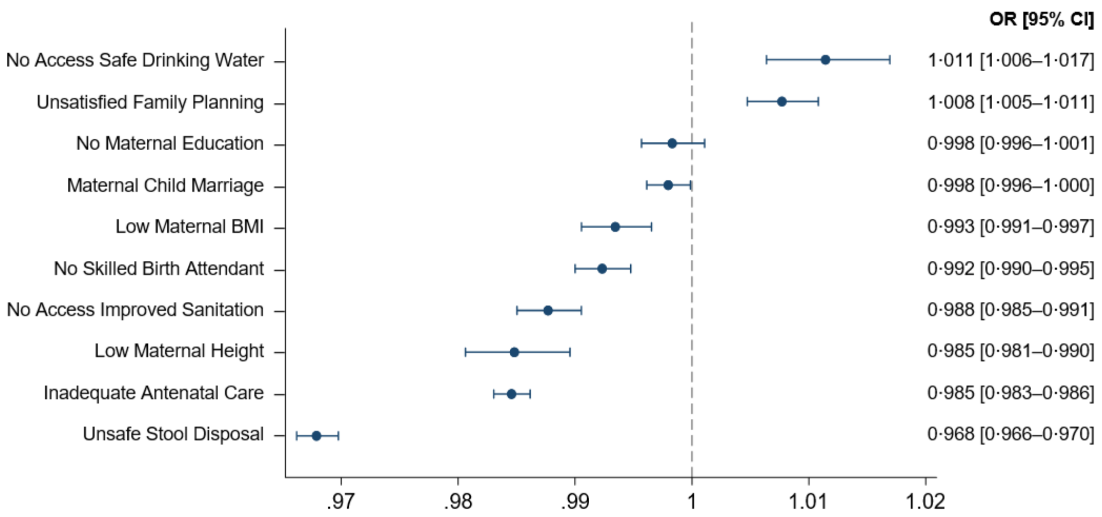
The three factors with the strongest correlations with economic growth were only weakly and ambiguously correlated with measures of child malnutrition. High Indoor Pollution through Solid Cooking Fuels was found to have a significant and positive association only with underweight (not robust to sensitivity tests), No Iodized Salt use showed a positive association with stunting, underweight and dietary diversity failure, and Unsafe Practices for Child's Stool Disposal was negatively associated with stunting, wasting, underweight, and dietary diversity failure.

Figure V.5: Associations between per-head GDP and contributing factors of malnutrition

(a) Immediate determinants of malnutrition



(b) Underlying determinants of malnutrition



Circles represent point estimates of odds ratios associated with immediate determinants of malnutrition (a) and underlying determinants of malnutrition (b). Horizontal bars indicate 95% confidence intervals. GDP=gross domestic product. ORT=oral rehydration therapy. N=834,572 (No Vitamin A Supplementation), N= 910,642 (Delayed Breastfeeding Initiation), N= 1,067,017 (Incidence of Infectious Diseases), N= 1,051,314 (Incomplete Course of Vaccination), N= 1,019,887 (No care Seeking for Suspected Pneumonia despite Cough), N= 1,041,452 (No Consumption of Oral Rehydration Solution despite Diarrhea), N= 977,267 (High Indoor Pollution through Solid Cooking Fuels), N= 419,397 (No Iodized Salt Use). N= 637,120 (Unsatisfied Family Planning Needs), N= 1,035,846 (Maternal Child Marriage), N= 1,138,568 (No Maternal Education), N= 1,077,132 (No Skilled Birth Attendant), N= 1,082,733 (No access to Safe Drinking Water), N= 826,307 (Low Maternal BMI), N= 902,576 (Low Maternal Height), N= 1,094,647 (No Access to Improved Sanitation Facilities), N= 970,018 (Inadequate Antenatal Care), N= 753,504 (Unsafe Practices for Child's Stool Disposal).

V.4 Discussion

To our knowledge, this study is the first to empirically test the path from economic growth to reductions in child malnutrition as illustrated in the 2020 UNICEF Conceptual Framework on Maternal and Child Nutrition. We found a very small and ambiguous association between economic growth and child undernutrition in the form of stunting, underweight, and wasting, which contrasts with the expectations from the UNICEF framework, but is in line with previous empirical findings.[5,12] In addition to using more and newer DHS, we extended the analysis by also considering child overnutrition, for which we found a moderate negative association, and dietary diversity failure, for which we found a moderate positive association. The latter could to some extent be driven by the increasing availability of ultra-processed foods in higher-income countries[23], which in the longer term could lead to increases in both under- and overnutrition. This double burden is already observed in many emerging countries.[25]

Among the various potential contributing factors of malnutrition tested, we found the strongest associations with undernutrition for factors related to the mothers' health and education, reproductive health services, and housing conditions, confirming previous research.[14] For dietary diversity failure, we found health-related practices to have the strongest associations, followed by mother's education and housing conditions, while overnutrition was strongly associated only with the mother's BMI. This suggests that there is significant scope for reducing child malnutrition through improving underlying determinants and, to a lesser extent, immediate determinants. However, this study suggests that it is important to distinguish between undernutrition, overnutrition, and dietary diversity failure as they respond differently to these contributing factors of malnutrition.

We further found that while the majority of these potential contributing factors were negatively associated with economic growth, this association was often statistically or economically insignificant, and some of them even showed positive correlations. This suggests that economic growth is overall rather weakly (and ambiguously) associated with most potential contributing factors to malnutrition, which breaks the causal chain from economic growth to reductions in child malnutrition already in the first link.

Vollmer and colleagues[5] put forward three potential reasons why economic growth does not automatically translate into improvements in child undernutrition. First, income growth could be unequally distributed, and thus poor households might benefit less or not at all from increases in aggregate per-head GDP. Second, if poor households benefit from economic growth, they might not necessarily invest additional income into improving their children's nutritional status. Third, income growth does not necessarily lead to investments in public infrastructure and services that help improve children's nutritional status. We provided some empirical evidence for the relevance of these channels by showing that indeed, increases in per-head GDP do not necessarily improve households' health-related behavior (e.g., Vitamin A Supplementation, No Care Seeking for Suspected Pneumonia despite Cough, Incomplete Course of Vaccination) or access to public services (e.g., No Access to Safe Drinking Water, Unsatisfied Family Planning Needs).

There are several limitations to this study, which we attempted to address. The first concerns the measurement of undernutrition, in particular underweight and wasting. Improvements in these outcomes might not necessarily indicate improved nutritional status but could also mirror a change in diet towards more sugar and animal fats.[26] Yet, this issue is less relevant for stunting, and our results are similar for all three measures of undernutrition. In addition, genetic differences in height and weight potential across populations from different countries might bias the results[26], yet we largely mitigate this concern by controlling for country fixed effects. Further issues are related to the sampling and quality of DHS and Penn World Tables. First, DHS data sets cover disproportionately less very poor countries, as these often lack the capacity to conduct surveys. Thus, external validity for countries not included in our sample is limited. Yet, a potential self-selection bias is mitigated by the inclusion of country fixed effects. Second, it's been shown that the quality of GDP measurement in the Penn World Tables is positively related to a country's level of economic development.[27] This issue is also mitigated by including country fixed effects. Finally, as explained in detail elsewhere[5], reverse causality could be a source of bias. Children's nutritional status could first directly and negatively affect per-head GDP (e.g., by reducing parents' labor hours when caring for malnourished children). Second, children's nutritional status could be a proxy for overall population health, which is known to affect the economic development of a country.[3,28,29] Yet such differences are absorbed by including country fixed effects. In addition, we control for a range of household, child, and mother covariates to further reduce potential bias. Concerns of potential reverse causality and unobserved heterogeneity were further mitigated through instrumental variable regressions

(Supplement Tables A3 and A5), which identify the causal effect of economic growth on our outcomes under assumptions detailed elsewhere.[5]

In summary, economic growth does not automatically translate into sizeable reductions of child malnutrition. One explanation may be that economic growth is only weakly and ambiguously correlated with improvements in the determinants of child malnutrition. Future research could focus on investigating why this link is weak, i.e., if it is caused by an unequal distribution of economic growth among the population, by household's preferences, or by a lack of government investments in related infrastructure and services. Financial resources created by economic growth should be used for targeted investments in those areas most strongly related to child malnutrition. We found that mothers' health and education, as well as health-related practices are the most important determinants of child malnutrition, and in particular undernutrition. Investments in the education and health system, especially targeted to girls and women, can contribute to significant reductions in child malnutrition in certain contexts.[30] This includes women's access to reproductive health services, like adequate antenatal care and skilled birth assistance. Further progress could be reached by facilitating access to improved sanitation. While economic growth is associated with a decrease in overweight and obesity, we did not find any clear evidence on the mechanism behind this relationship, leaving scope for further empirical research.

V.5 Appendix

Supplement Table V.A1: Number of surveys and most recent survey year per country

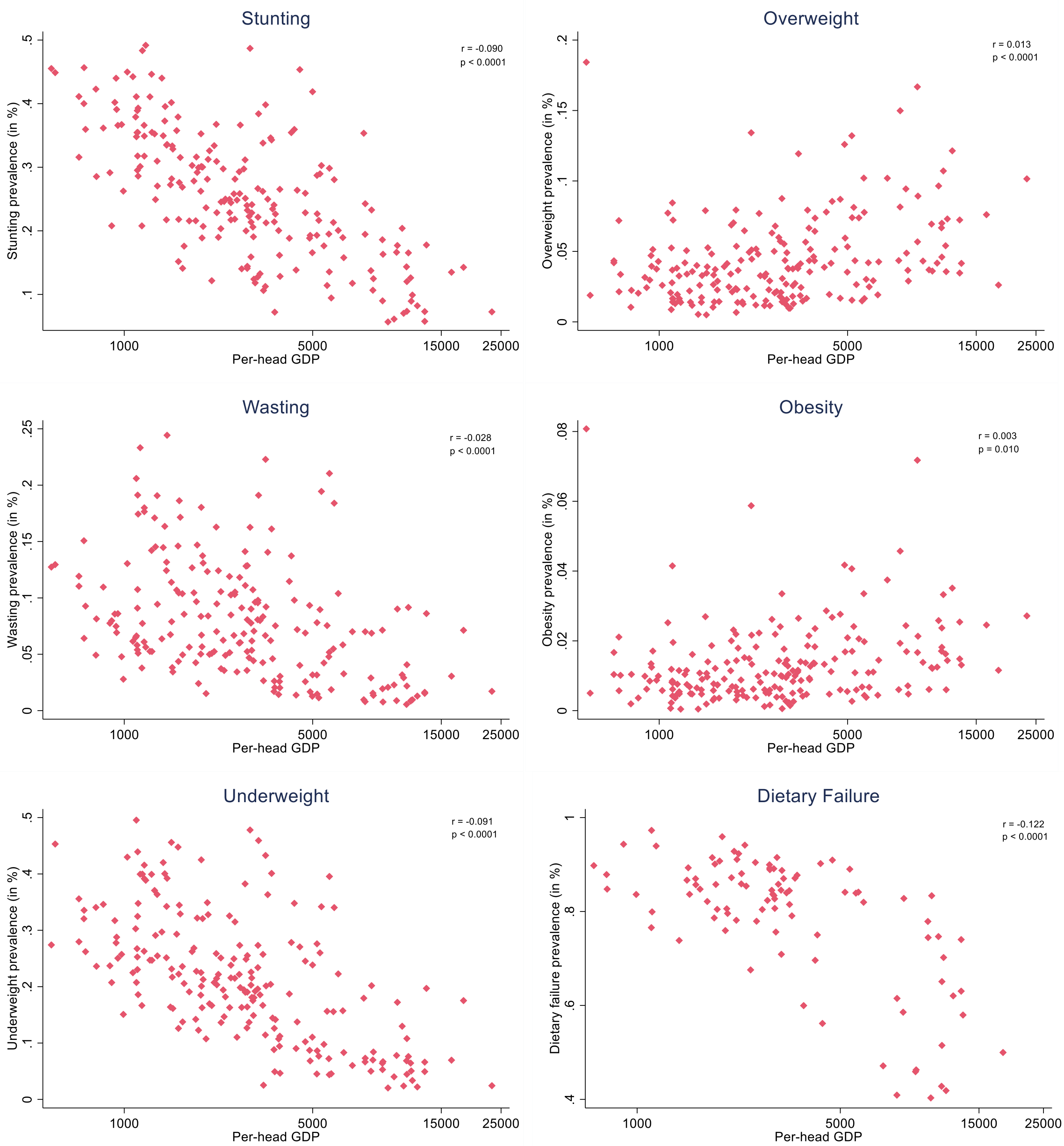
Country	Number of surveys	Most recent survey year
Albania	2	2018
Angola	3	2015
Armenia	4	2016
Bangladesh	5	2014
Benin	5	2018
Bolivia	2	2008
Burkina Faso	4	2010
Burundi	3	2017
Cambodia	4	2014
Cameroon	5	2018
Chad	3	2015
Colombia	4	2015
Comoros	2	2012
Congo	2	2012
Congo Democratic Republic	2	2014
Cote d'Ivoire	3	2012
Dominican Republic	6	2013
Egypt	5	2014
Ethiopia	5	2019
Gabon	2	2012
Gambia	2	2020
Ghana	6	2016
Guatemala	3	2015
Guinea	5	2021
Haiti	5	2017
Honduras	2	2012
India	3	2020
Jordan	5	2018
Kazakhstan	2	1999
Kenya	5	2020
Kyrgyz Republic	2	2012
Lesotho	3	2014
Liberia	6	2020
Madagascar	7	2016
Malawi	7	2017
Maldives	2	2017
Mali	5	2018
Morocco	2	2004
Mozambique	5	2018
Namibia	4	2013
Nepal	3	2016
Nicaragua	2	2001
Niger	4	2012
Nigeria	7	2018
Pakistan	2	2018
Peru	8	2012
Rwanda	7	2020
Senegal	11	2019
Sierra Leone	4	2019
Tajikistan	2	2017
Tanzania	9	2017
Timor-Leste	2	2016
Togo	3	2017
Turkey	3	2013
Uganda	7	2016
Yemen	2	2013
Zambia	6	2018
Zimbabwe	5	2015

Supplement Table V.A2: Definition of contributing factors of malnutrition

Contributing factor	**Description**
Enabling Environments	
No Access to Safe Drinking Water	=1 if household does not have access to water piped into dwelling, yard or plot, public tab of standpipe, tube well or borehole, or protected well
No Access to Improved Sanitation Facilities	=1 if household does not have access to flush toilet, septic tank, or pit latrine
Unsafe Practices for Child's Stool Disposal	=1 if child does not use toilet/latrine, if fecal matter is not disposed by toilet/latrine, disposable diaper or burying
Inadequate Antenatal Care	=1 if mother had less than 4 antenatal care visits from a skilled provider for most recent birth
No Skilled Birth Attendant	=1 if child was delivered without skilled birth attendants (e.g., physicians, nurses, midwives)
Unsatisfied Family Planning Needs	=1 if mother wishes to stop/delay childbearing, but is not using any modern contraception method
Maternal Child Marriage	=1 if mother was married before age 18
No Maternal Education	=1 if mother has no formal education
Low Maternal Height	=1 if mother's height is less than 145cm/155cm
Low/High Maternal BMI	=1 if mother's BMI is less than 18·5 / more than 25·0
Proximal Components	
Delayed Breastfeeding Initiation	=1 if mother started breastfeeding of child later than one hour after birth
No Vitamin A Supplementation	=1 if child did not receive vitamin A supplement in past 6 months
No Iodized Salt Use	=1 if household does not use iodized salt
Incomplete Course of Vaccination	=1 if child is not fully vaccinated against all following diseases: tuberculosis, diphtheria, pertusis, tetanus, polio, measles
Incidence of Infectious Diseases	=1 if child had diarrhea, cough, or fever in the past 2 weeks
No Consumption of Oral Rehydration Solution despite Diarrhea	=1 if child had diarrhea recently but did not receive oral rehydration therapy
No care Seeking for Suspected Pneumonia despite Cough	=1 if child had cough in past two weeks and no treatment was sought
High Indoor Pollution through Solid Cooking Fuels	=1 if household uses solid cooking fuels (e.g., coal/lignite, charcoal, wood, straw/shrub/grass, agricultural crops, animal dung)

BMI=body mass index (calculated as weight in kilograms divided by height in meters squared).

Supplement Figure V.A1: Correlation between the prevalence of early childhood malnutrition and log of per-head GDP



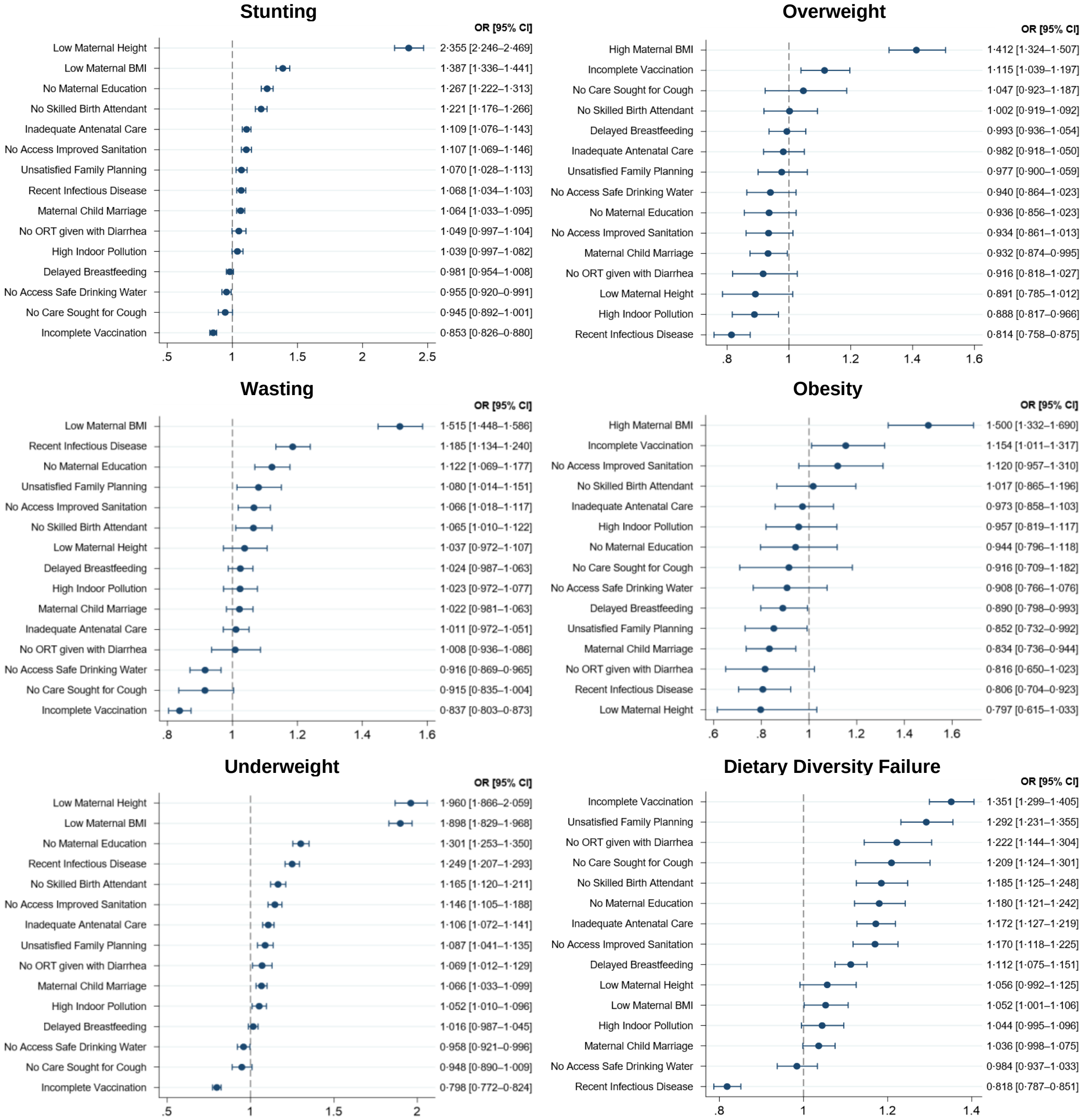
n=206 surveys (207 for stunting, 96 for dietary diversity failure). GDP=gross domestic product.

Supplement Table V.A3: Association between economic growth and malnutrition – robustness tests

	Stunting	Wasting	Underweight	Overweight	Obesity	Dietary Diversity Failure
Unweighted						
Log of per-head GDP	-0·0011	0·0005	0·0001	-0·0011	-0·0006	0·0033
(SE)	(0·0002)	(0·0001)	(0·0002)	(0·0001)	(0·0001)	(0·0005)
p value	<0·001	<0·001	0·766	<0·001	<0·001	<0·001
Number of observations	899,531	900,246	896,593	900,246	900,246	536,649
Weighted						
Log of per-head GDP	-0·0027	0·0003	0·0002	-0·0025	-0·0012	0·0040
(SE)	(0·0003)	(0·0002)	(0·0003)	(0·0002)	(0·0002)	(0·0005)
p value	<0·001	0·131	0·400	<0·001	<0·001	<0·001
Number of observations	899,531	900,246	896,593	900,246	900,246	536,649
Trimmed						
Log of per-head GDP	-0·0010	-0·0002	0·0001	-0·0002	-0·0001	0·0032
(SE)	(0·0002)	(0·0001)	(0·0002)	(0·0001)	(0·0001)	(0·0006)
p value	<0·001	0·215	0·654	0·060	0·034	<0·001
Number of observations	871,913	683,221	845,741	857,824	865,145	520,930
Instrumental Variable						
Log of per-head GDP	-0·0133	0·0040	0·0394	-0·0219	-0·0096	-0·0091
(SE)	(0·0083)	(0·0052)	(0·0107)	(0·0042)	(0·0021)	(0·0024)
p value	0·111	0·434	<0·001	<0·001	<0·001	<0·001
Number of observations	899,009	899,685	896,071	899,685	899,685	536,649

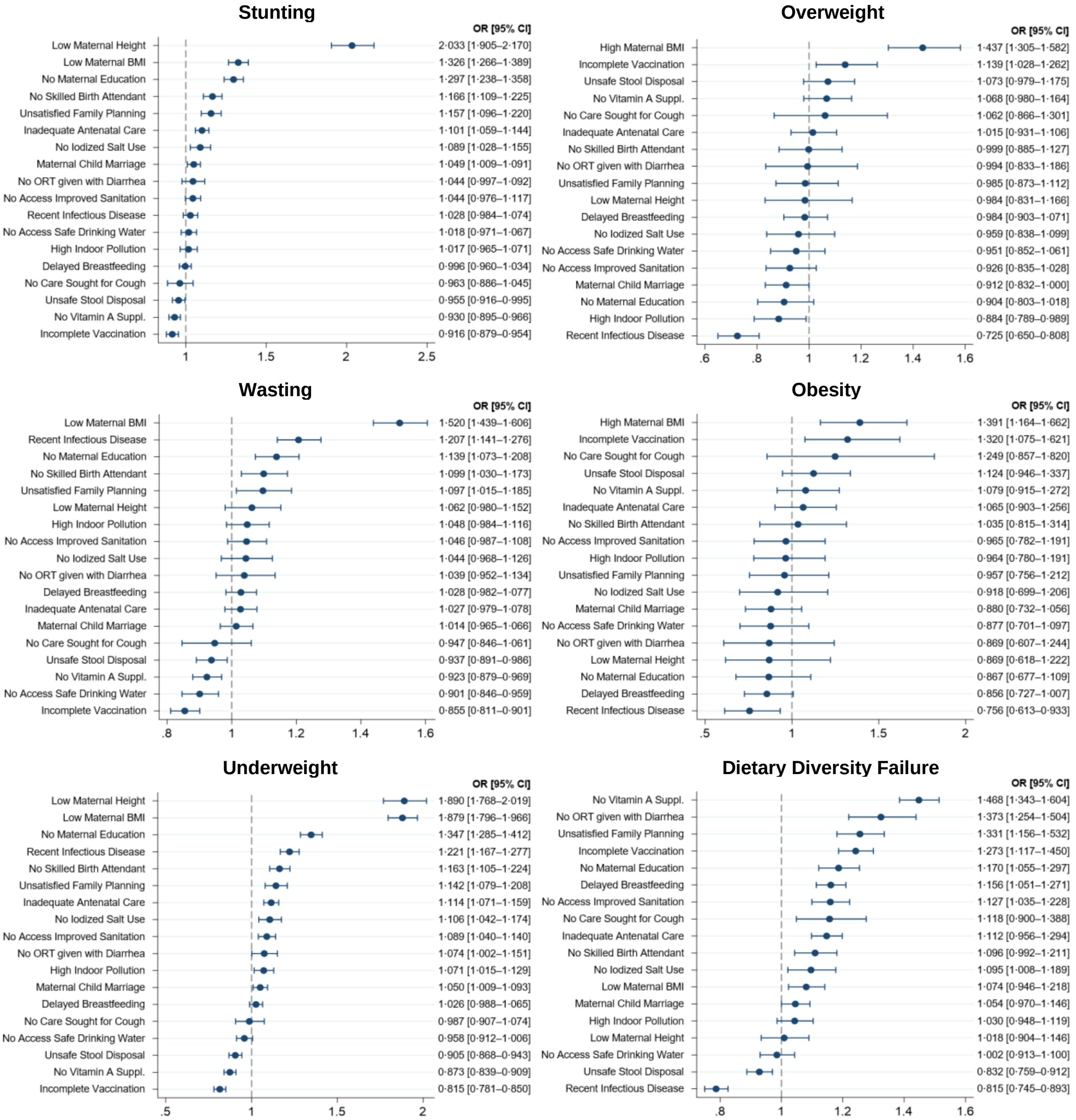
Data for the per-head gross domestic product (GDP) were merged with Demographic and Health Survey data by survey year. All regressions are ordinary least squares, and the instrumental variable regressions are two-stage least squares. All specifications include country and survey-year fixed effects as well as household and child/mother control variables. SEs are clustered at the PSU level. Coefficients for the log of per-head GDP represent a 5% increase in per-head GDP. In the instrumental variable regressions, we used the variable share of gross capital formation at present purchasing power parity (investment share of GDP) from the Penn World Tables 10.0, with a 5-year lag as an instrument for the log of the per-head GDP.

Supplement Figure V.A2: Association between determinants and indicators of malnutrition – standard model (15 determinants)



Circles represent point estimates of odds ratios associated with the various measures of malnutrition. Horizontal bars indicate 95% confidence intervals. BMI=body mass index (calculated as weight in kilograms divided by height in meters squared). ORT=oral rehydration therapy. N=135,310; Countries=56 (stunting). N=135,669; Countries=56 (wasting). N=135,567; Countries=56 (underweight). N=135,669; Countries=56 (overweight). N=134,079; Countries=55 (obesity). N=98,842; Countries=51 (dietary diversity failure).

Supplement Figure V.A3: Association between determinants and indicators of malnutrition – extended model (18 determinants)



Circles represent point estimates of odds ratios associated with the various measures of malnutrition. Horizontal bars indicate 95% confidence intervals. BMI=body mass index (calculated as weight in kilograms divided by height in meters squared). ORT=oral rehydration therapy. N=72,411; Countries=36 (stunting). N=72,467; Countries=36 (wasting). N=72,411; Countries=36 (underweight). N=72,467; Countries=36 (overweight). N=72,467; Countries=36 (obesity). N=73,262; Countries=36 (dietary diversity failure).

Supplement Table V.A4 (I): Association between determinants and indicators of malnutrition – sanity tests

	Stunting			Wasting			Underweight		
	Un-weigh-ted	**Weigh-ted**	**Trim-med**	**Un-weigh-ted**	**Weigh-ted**	**Trim-med**	**Un-weigh-ted**	**Weigh-ted**	**Trim-med**
Delayed Breastfeeding	-0·002	0·001	-0·003	0·003	-0·001	0·002	0·005	0·000	0·004
(SE)	(0·002)	(0·004)	(0·002)	(0·002)	(0·003)	(0·002)	(0·002)	(0·004)	(0·002)
p value	0·313	0·847	0·249	0·107	0·598	0·184	0·046	0·986	0·069
Incomplete Vaccination	-0·022	-0·016	-0·021	-0·016	-0·021	-0·016	-0·026	-0·028	-0·026
(SE)	(0·003)	(0·005)	(0·003)	(0·002)	(0·003)	(0·002)	(0·003)	(0·005)	(0·003)
p value	<0·001	0·001	<0·001	<0·001	<0·001	<0·001	<0·001	<0·001	<0·001
Recent Infectious Disease	0·010	0·017	0·009	0·015	0·017	0·015	0·032	0·038	0·032
(SE)	(0·003)	(0·005)	(0·003)	(0·002)	(0·003)	(0·002)	(0·003)	(0·005)	(0·003)
p value	0·001	<0·001	0·002	<0·001	<0·001	<0·001	<0·001	<0·001	<0·001
No ORT given with Diarrhea (SE)	0·007 (0·004)	0·013 (0·008)	0·006 (0·004)	-0·000 (0·003)	-0·006 (0·006)	-0·001 (0·003)	0·008 (0·004)	0·015 (0·009)	0·008 (0·004)
p value	0·098	0·125	0·149	0·902	0·263	0·863	0·050	0·072	0·065
No Care Sought for Cough	-0·011	-0·012	-0·010	-0·009	-0·000	-0·009	-0·014	-0·003	-0·013
(SE)	(0·005)	(0·009)	(0·005)	(0·003)	(0·007)	(0·003)	(0·004)	(0·009)	(0·004)
p value	0·015	0·199	0·030	0·004	0·956	0·003	0·002	0·766	0·003
High Indoor Pollution	-0·008	0·005	-0·009	-0·009	-0·004	-0·008	-0·008	-0·003	-0·008
(SE)	(0·003)	(0·006)	(0·003)	(0·002)	(0·004)	(0·002)	(0·003)	(0·006)	(0·003)
p value	0·014	0·426	0·011	0·000	0·328	<0·001	0·014	0·638	0·012
No Access Safe Drinking	0·019	0·014	0·019	0·008	0·002	0·008	0·026	0·018	0·026
Water (SE)	(0·003)	(0·005)	(0·003)	(0·002)	(0·004)	(0·002)	(0·003)	(0·005)	(0·003)
p value	<0·001	0·005	<0·001	0·001	0·664	0·001	<0·001	0·001	<0·001
No Access Improved	0·018	0·024	0·018	0·001	0·003	0·001	0·016	0·016	0·016
Sanitation (SE)	(0·003)	(0·004)	(0·003)	(0·002)	(0·003)	(0·002)	(0·003)	(0·004)	(0·003)
p value	<0·001	<0·001	<0·001	0·523	0·359	0·461	<0·001	<0·001	<0·001
Inadequate Antenatal Care	0·038	0·034	0·038	0·004	0·009	0·004	0·023	0·031	0·023
(SE)	(0·004)	(0·006)	(0·004)	(0·002)	(0·004)	(0·003)	(0·003)	(0·006)	(0·003)
p value	<0·001	<0·001	<0·001	0·109	0·041	0·121	0·000	0·000	0·000
No Skilled Birth Attendant	0·011	0·009	0·012	0·004	0·015	0·004	0·013	0·018	0·013
(SE)	(0·003)	(0·006)	(0·003)	(0·002)	(0·004)	(0·002)	(0·003)	(0·006)	(0·003)
p value	0·001	0·147	<0·001	0·072	<0·001	0·066	<0·001	0·005	<0·001
Unsatisfied Family Planning	0·011	0·010	0·011	0·002	0·004	0·002	0·011	0·007	0·010
(SE)	(0·003)	(0·004)	(0·003)	(0·002)	(0·003)	(0·002)	(0·002)	(0·004)	(0·003)
p value	<0·001	0·020	<0·001	0·197	0·150	0·305	<0·001	0·089	<0·001
Maternal Child Marriage	0·010	0·010	0·010	0·007	0·006	0·006	0·017	0·017	0·016
(SE)	(0·003)	(0·006)	(0·003)	(0·003)	(0·004)	(0·003)	(0·003)	(0·006)	(0·003)
p value	0·002	0·085	0·003	0·013	0·155	0·020	<0·001	0·005	<0·001
No Maternal Education	0·049	0·060	0·049	0·015	0·018	0·015	0·053	0·059	0·053
(SE)	(0·004)	(0·005)	(0·004)	(0·003)	(0·004)	(0·003)	(0·003)	(0·005)	(0·003)
p value	<0·001	<0·001	<0·001	<0·001	<0·001	<0·001	<0·001	<0·001	<0·001
Low Maternal Height	0·178	0·168	0·179	0·005	0·006	0·005	0·129	0·136	0·131
(SE)	(0·005)	(0·008)	(0·005)	(0·004)	(0·005)	(0·004)	(0·005)	(0·007)	(0·005)
p value	<0·001	<0·001	<0·001	0·202	0·238	0·215	<0·001	<0·001	<0·001
Low Maternal BMI	0·066	0·064	0·068	0·057	0·054	0·057	0·135	0·134	0·136
(SE)	(0·004)	(0·006)	(0·004)	(0·003)	(0·004)	(0·003)	(0·004)	(0·006)	(0·004)
p value	<0·001	<0·001	<0·001	<0·001	<0·001	<0·001	<0·001	<0·001	<0·001
Number of observations	135,310	135,310	131,580	135,669	135,669	131,506	135,567	135,567	131,837

BMI=body mass index (calculated as weight in kilograms divided by height in meters squared). ORT=oral rehydration therapy. All regressions are ordinary least squares. All specifications are ordinary least squares and include country-fixed effects as well as household and child/mother control variables. SEs are clustered at the PSU level.

Supplement Table V.A4 (II): Association between determinants and indicators of malnutrition – sanity tests

	Overweight			Obesity			Dietary Diversity Failure		
	Un-weigh-ted	Weigh-ted	Trim-med	Un-weigh-ted	Weigh-ted	Trim-med	Un-weigh-ted	Weigh-ted	Trim-med
Delayed Breastfeeding	0·000	-0·000	0·000	-0·001	-0·001	-0·001	0·015	0·009	0·015
(SE)	(0·001)	(0·001)	(0·001)	(0·001)	(0·001)	(0·001)	(0·003)	(0·004)	(0·003)
p value	0·921	0·781	0·909	0·057	0·121	0·068	0·000	0·015	<0·001
Incomplete Vaccination	0·009	0·008	0·009	0·003	0·004	0·003	0·051	0·033	0·050
(SE)	(0·001)	(0·001)	(0·001)	(0·001)	(0·001)	(0·001)	(0·003)	(0·005)	(0·004)
p value	<0·001	<0·001	<0·001	<0·001	<0·001	<0·001	<0·001	<0·001	<0·001
Recent Infectious Disease	-0·008	-0·009	-0·009	-0·003	-0·003	-0·003	-0·028	-0·019	-0·028
(SE)	(0·001)	(0·002)	(0·001)	(0·001)	(0·001)	(0·001)	(0·003)	(0·005)	(0·003)
p value	<0·001	<0·001	<0·001	<0·001	0·004	<0·001	<0·001	<0·001	<0·001
No ORT given with Diarrhea (SE)	-0·003 (0·002)	-0·004 (0·002)	-0·004 (0·002)	-0·002 (0·001)	-0·003 (0·001)	-0·002 (0·001)	0·033 (0·005)	0·030 (0·007)	0·033 (0·005)
p value	0·079	0·137	0·067	0·044	0·027	0·044	<0·001	<0·001	<0·001
No Care Sought for Cough	0·001	0·006	0·001	-0·001	0·001	-0·001	0·026	0·018	0·026
(SE)	(0·002)	(0·004)	(0·002)	(0·001)	(0·002)	(0·001)	(0·006)	(0·009)	(0·006)
p value	0·731	0·108	0·785	0·387	0·569	0·368	<0·001	0·042	<0·001
High Indoor Pollution	-0·002	-0·003	-0·002	-0·001	-0·001	-0·001	-0·005	0·005	-0·004
(SE)	(0·001)	(0·002)	(0·001)	(0·001)	(0·001)	(0·001)	(0·004)	(0·005)	(0·004)
p value	0·107	0·067	0·074	0·236	0·164	0·180	0·200	0·318	0·234
No Access Safe Drinking Water (SE)	-0·001 (0·001)	-0·003 (0·002)	-0·001 (0·001)	0·001 (0·001)	0·000 (0·001)	0·001 (0·001)	0·021 (0·003)	0·021 (0·005)	0·022 (0·003)
p value	0·317	0·084	0·257	0·041	0·657	0·067	<0·001	<0·001	<0·001
No Access Improved Sanitation (SE)	-0·001 (0·001)	-0·002 (0·001)	-0·001 (0·001)	-0·001 (0·001)	-0·002 (0·001)	-0·001 (0·001)	0·022 (0·003)	0·025 (0·004)	0·022 (0·003)
p value	0·310	0·266	0·304	0·346	0·055	0·260	<0·001	<0·001	<0·001
Inadequate Antenatal Care	-0·000	0·001	-0·001	0·000	0·000	0·000	0·023	0·009	0·023
(SE)	(0·001)	(0·002)	(0·001)	(0·001)	(0·001)	(0·001)	(0·004)	(0·005)	(0·004)
p value	0·891	0·517	0·571	0·763	0·799	0·947	<0·001	0·090	<0·001
No Skilled Birth Attendant	0·000	0·000	0·000	-0·001	-0·000	-0·001	0·034	0·022	0·033
(SE)	(0·002)	(0·002)	(0·002)	(0·001)	(0·001)	(0·001)	(0·004)	(0·006)	(0·004)
p value	0·880	0·832	0·770	0·081	0·724	0·129	<0·001	<0·001	<0·001
Unsatisfied Family Planning	-0·002	-0·002	-0·002	-0·002	-0·002	-0·002	0·006	0·008	0·007
(SE)	(0·001)	(0·002)	(0·001)	(0·001)	(0·001)	(0·001)	(0·003)	(0·004)	(0·003)
p value	0·037	0·143	0·105	0·004	0·002	0·010	0·025	0·055	0·021
Maternal Child Marriage	-0·003	-0·004	-0·003	-0·000	-0·000	-0·000	0·008	0·005	0·007
(SE)	(0·002)	(0·002)	(0·002)	(0·001)	(0·001)	(0·001)	(0·004)	(0·006)	(0·004)
p value	0·029	0·058	0·036	0·994	0·891	0·973	0·035	0·459	0·065
No Maternal Education	-0·002	-0·003	-0·002	-0·000	-0·001	-0·000	0·021	0·025	0·022
(SE)	(0·001)	(0·002)	(0·001)	(0·001)	(0·001)	(0·001)	(0·004)	(0·005)	(0·004)
p value	0·240	0·111	0·264	0·573	0·520	0·530	<0·001	<0·001	<0·001
Low Maternal Height	-0·004	-0·002	-0·004	-0·002	-0·001	-0·002	0·011	0·008	0·010
(SE)	(0·002)	(0·002)	(0·002)	(0·001)	(0·001)	(0·001)	(0·005)	(0·006)	(0·005)
p value	0·063	0·279	0·063	0·074	0·176	0·077	0·030	0·192	0·044
Low Maternal BMI							0·010	0·011	0·011
(SE)							(0·004)	(0·005)	(0·004)
p value							0·005	0·030	0·005
High Maternal BMI	0·014	0·012	0·014	0·005	0·004	0·005			
(SE)	(0·001)	(0·002)	(0·001)	(0·001)	(0·001)	(0·001)			
p value	<0·001	<0·001	<0·001	<0·001	<0·001	<0·001			
Number of observations	135,669	135,669	134,207	134,079	134,079	133,555	98,842	98,842	94,962

BMI=body mass index (calculated as weight in kilograms divided by height in meters squared). ORT=oral rehydration therapy. All regressions are ordinary least squares. All specifications are ordinary least squares and include country-fixed effects as well as household and child/mother control variables. SEs are clustered at the PSU level.

Supplement Table V.A5 (I): Association between economic growth and determinants of malnutrition – sanity tests

	Delayed Breast-feeding	No Vitamin A Suppl·	No Iodized Salt Use	Incomplete Vaccination	Recent Infectious Disease	No ORT given with Diarrhea	No Care Sought for Cough	High Indoor Pollution
Unweighted								
Log of per-head GDP	0·0025	-0·0015	-0·0328	0·0004	0·0019	-0·0004	0·0008	-0·0048
(SE)	(0·0003)	(0·0003)	(0·0016)	(0·0002)	(0·0002)	(0·0001)	(0·0001)	(0·0002)
p value	<0·001	<0·001	<0·001	0·062	<0·001	0·004	<0·001	<0·001
Number of observations	910,642	834,572	419,397	1,051,314	1,067,017	1,041,452	1,019,887	977,267
Weighted								
Log of per-head GDP	0·0032	-0·0015	-0·0550	-0·0005	0·0015	-0·0006	-0·0003	-0·0036
(SE)	(0·0003)	(0·0004)	(0·0014)	(0·0002)	(0·0003)	(0·0002)	(0·0001)	(0·0004)
p value	<0·001	<0·001	<0·001	0·021	<0·001	<0·001	0·061	<0·001
Number of observations	910,642	834,572	419,397	1,051,314	1,067,017	1,041,452	1,019,887	977,267
Trimmed								
Log of per-head GDP	0·0025	-0·0023	-0·0305	0·0001	0·0012	-0·0001	0·0008	-0·0051
(SE)	(0·0003)	(0·0004)	(0·0017)	(0·0002)	(0·0002)	(0·0001)	(0·0001)	(0·0002)
p value	<0·001	<0·001	<0·001	0·508	<0·001	0·368	<0·001	<0·001
Number of observations	883,445	824,240	414,444	1,016,255	1,048,261	1,005,715	876,281	940,003
Instrumental Variable								
Log of per-head GDP	0·0130	-0·0514	0·0138	-0·0130	0·0210	0·0038	0·0021	0·0085
(SE)	(0·0056)	(0·0037)	(0·0194)	(0·0054)	(0·0033)	(0·0018)	(0·0017)	(0·0063)
p value	0·019	<0·001	0·478	0·016	<0·001	0·038	0·207	0·177
Number of observations	910,642	833,883	419,397	1,050,158	1,065,511	1,040,450	1,019,229	972,927

ORT=oral rehydration therapy. Data for per-head gross domestic product (GDP) were merged with Demographic and Health Survey data by survey year. All regressions are ordinary least squares, and the instrumental variable regressions are two-stage least squares. All specifications include country and survey-year fixed effects as well as household control variables. SEs are clustered at the PSU level. Coefficients for the log of per-head GDP represent a 5% increase in per-head GDP. In the instrumental variable regressions, we used the variable share of gross capital formation at present purchasing power parity (investment share of GDP) from the Penn World Tables 10.0, with a 5-year lag as an instrument for the log of the per-head GDP.

Supplement Table V.A5 (II): Association between economic growth and determinants of malnutrition – sanity tests

	No Access Safe Drinking Water	No Access Improved Sanitation	Unsafe Stool Disposal	Inadequate Antenatal Care	No Skilled Birth Attendant	Unsatisfied Family Planning	Maternal Child Marriage	No Maternal Educ·	Low Maternal Height	Low Maternal BMI
Unweighted										
Log of per-head GDP	0·0018	-0·0021	-0·0096	-0·0027	-0·0004	0·0016	-0·0003	-0·0001	-0·0008	-0·0009
(SE)	(0·0003)	(0·0003)	(0·0005)	(0·0002)	(0·0002)	(0·0003)	(0·0002)	(0·0002)	(0·0001)	(0·0002)
p value	<0·001	<0·001	<0·001	<0·001	0·082	<0·001	0·149	0·522	<0·001	<0·001
Number of observations	1,082,733	1,094,647	753,504	970,018	1,077,132	637,120	1,035,846	1,138,568	902,576	826,307
Weighted										
Log of per-head GDP	-0·0027	-0·0027	-0·0101	-0·0006	0·0006	0·0007	0·0009	-0·0000	-0·0008	-0·0009
(SE)	(0·0005)	(0·0004)	(0·0007)	(0·0003)	(0·0003)	(0·0004)	(0·0003)	(0·0003)	(0·0001)	(0·0002)
p value	<0·001	<0·001	<0·001	0·048	0·090	0·084	0·003	0·972	<0·001	<0·001
Number of observations	1,082,733	1,094,647	753,504	970,018	1,077,132	637,120	1,035,846	1,138,568	902,576	826,307
Trimmed										
Log of per-head GDP	0·0014	-0·0018	-0·0076	-0·0027	-0·0005	0·0017	-0·0003	0·0003	-0·0006	-0·0003
(SE)	(0·0003)	(0·0003)	(0·0005)	(0·0002)	(0·0003)	(0·0003)	(0·0002)	(0·0002)	(0·0001)	(0·0002)
p value	<0·001	<0·001	<0·001	<0·001	0·039	<0·001	0·200	0·170	<0·001	0·070
Number of observations	1,052,950	1,045,435	733,816	940,669	1,047,046	543,821	1,005,954	1,107,621	877,445	753,075
Instrumental Variable										
Log of per-head GDP	-0·0748	-0·0513	-0·0375	-0·0036	0·0981	0·4495	0·0115	0·0166	0·0010	0·0010
(SE)	(0·0099)	(0·0052)	(0·0033)	(0·0028)	(0·0091)	(0·3455)	(0·0039)	(0·0039)	(0·0011)	(0·0017)
p value	<0·001	<0·001	<0·001	0·204	<0·001	0·193	0·003	<0·001	0·373	0·551
Number of observations	1,077,165	1,089,079	753,504	964,891	1,075,934	637,120	1,034,645	1,136,720	902,576	826,307

BMI=body mass index (calculated as weight in kilograms divided by height in meters squared). Data for the per-head gross domestic product (GDP) were merged with Demographic and Health Survey data by survey year. All regressions are ordinary least squares, and the instrumental variable regressions are two-stage least squares. All specifications include country and survey-year fixed effects as well as household control variables. SEs are clustered at the PSU level. Coefficients for the log of per-head GDP represent a 5% increase in per-head GDP. In the instrumental variable regressions, we used the variable share of gross capital formation at present purchasing power parity (investment share of GDP) from the Penn World Tables 10.0, with a 5-year lag as an instrument for the log of the per-head GDP

Chapter VI

The Impact of Mobility Restrictions on Labor Markets: Evidence from Nationally Representative Phone Surveys during the COVID-19 Pandemic in Kenya

With: Moritz Schreckenberger and Utz Johann Pape

Abstract

The COVID-19 pandemic affected people's livelihoods in many ways, particularly in developing countries. This paper examined the degree to which recovering mobility levels impacted labor market outcomes in Kenya over the course of the pandemic, starting from May 2020 until June 2021. We used an instrumental variable approach to identify the causal impacts of mobility reduction induced by policy changes on labor market outcomes. We show that a 10 percent recovery of mobility led to a 8 percentage points increase in household members being employed. At the same time, a 10 percent recovery of mobility caused an increase of about 5.7 wage hours per week (formal and informal). Among the factors influencing self-reported mobility-reducing behavior, trust in the government's ability to deal with the pandemic correlated with less self-reported mobility reduction, while people who knew someone with an infection tended to reduce mobility less. Finally, countrywide policy stringency levels clearly reduced self-reported mobility. Given the demonstrated adverse impacts of reducing mobility on economic indicators, the government should explore options to limit the economic fall-out while protecting citizens from infections, for example, by using partial or geographically constrained lockdowns.

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VI.1 Introduction

The Coronavirus-19 (COVID-19) pandemic has been an unprecedented situation for the globalized world. By the end of 2021, estimates stood at more than 230 million people having been infected and around 4.7 million people have died from the COVID-19 pandemic across the globe.[1,2] At the same time, the pandemic has had significant labor market effects, with an estimated 225 million full-time jobs lost worldwide between the fourth quarter of 2019 and the first quarter of 2021 alone.[3] These COVID-19-related labor market costs were driven by many factors, such as peoples' behavior in uncertain times as well as the policies and guidelines governments impose to curb the spread of the virus.

As a response to the pandemic, many governments imposed two types of measures. Firstly, measures aimed at restricting mobility and social interaction to reduce the speed of further infection as well as secondly, measures to mitigate the economic consequences on businesses and households. The consequences of the pandemic and restrictions on personal mobility have severely disrupted economic activities, as between one and four in five workers resided in countries with required workplace closures.[3]

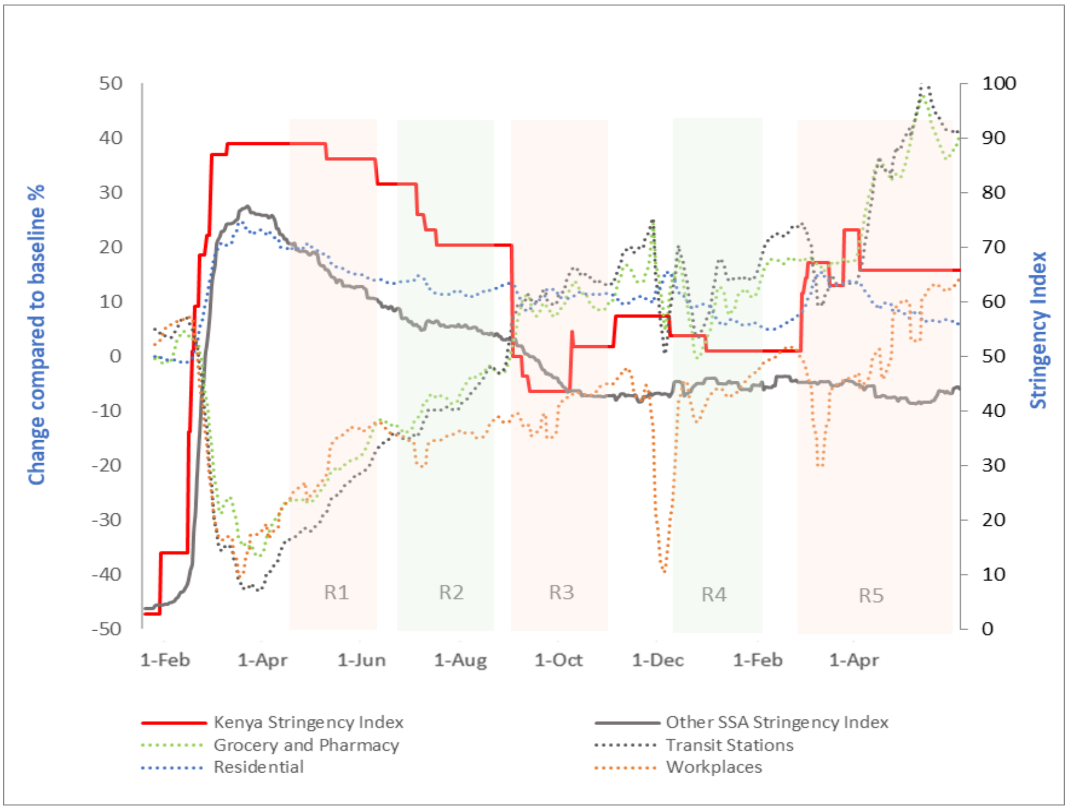
Particularly for households in developing countries, the labor market implications of the pandemic were potentially dire. The lack of economic safety nets, particularly in the informal sector as well as increased risk of infection and related expenses, especially for poor people living in high-density areas, exacerbated the consequences of losing parts of the income or the job entirely.[4-6] Given the additional challenges households in developing countries face in coping with such a crisis, it is elementary for policymakers to understand which trade-offs and socio-economic consequences countermeasures may imply. As governments react to health crises such as the different waves of Covid-19 infections and impose restrictions to save lives, people subsequently change their behavior (e.g., reduce mobility) and this in turn affects labor markets. Therefore, a better understanding of the causal relationships between human behavior and labor market outcomes is vital to crafting better, more effective and targeted policies. This will be relevant in all future situations in which there is the joint goal of reducing human interaction to save lives while minimizing the negative economic and societal costs.

Kenya's first case of COVID-19 was recorded in March 2020. Reported infections rapidly increased, peaking on October 31, 2020 with 1,395 new infections per day.[7] Following Kenya's first case of confirmed COVID-19 in March 2020, the Government of Kenya quickly put in place multiple policies and measures to contain the spread of the virus. In March 2020 for instance, the Government of Kenya introduced a series of restrictions ranging from the closure of educational institutions to directing public and private sector workers to home-based work, except for essential workers.[8-10] Entry into Kenya was limited to citizens and residents but required quarantine for 14 days, while local air travel was suspended and resumed on July 15. These measures were followed by fast reductions in average mobility outside of residential areas but with an increase in residential movement (Figure 1).

Many studies in different contexts have shown that COVID-19-related containment measures aiming to reduce mobility and social contacts were a key tool in slowing the spread of the virus. Multiple studies have proven these policies' successes in reducing mobility compared to pre-COVID-19 levels.[11-14] The successful reduction of mobility has also been linked to positive effects such as saving lives, buying time to develop vaccines and flattening the curve such that a country's health infrastructures were better able to cope with the demand.[15,16] However, as the disease was better understood, socio-economic effects of the COVID-19 pandemic started receiving increased attention. Multiple studies have looked into COVID-19 effects on different dimensions of household livelihoods both in the developed world[17-19] as well as in developing countries.[20,21] Using data from high-frequency phone surveys, Khamis et al. (2021) for example estimated the early impact of COVID-19 on the labor markets of 39 countries. Their findings showed that the pandemic had negatively affected labor market outcomes in these countries (job and income losses, lack of payment, job changes), with more pronounced impacts among workers in manufacturing (40%) and services (38%) than in agriculture (22%) as well as among self-employed (46%) compared to employees (39%).

While there is extensive literature on the aggregated socio-economic effects of the COVID-19 pandemic both in developed countries as well as developing countries, including Kenya[22-24], less research has been conducted looking into the specific mechanisms through which the pandemic affected labor market outcomes in developing countries. In particular, the channel of changing mobility has not been investigated extensively yet, most likely due to both measurement difficulties and identification issues. Mobility is an outcome of labor market activity as well as something that drives labor market activity, for example, by providing jobs in the transportation sector. Likewise, the ability to move determines whether people have access to markets to sell their goods, as well as whether customers can attain the goods that they would like to acquire. Finally, supply chains, as well as trade, rely on mobility, which in turn may impact production and thus, labor markets further downstream.[25] Mobility was severely impacted by policies aimed at curbing the spread of the virus in Kenya, which presents a natural experiment over the course of the pandemic. We intend to leverage this experiment to quantify the changes in labor market outcomes that were driven by changing mobility levels by applying instrumental variable analyses.

Figure VI.1: Development of Kenyan Policy Stringency and Mobility Types (Feb 20 – Jul 21)



Source: Authors' calculations

Figure 1 shows how the nationwide policy stringency and different types of mobility changed between the beginning of the pandemic and July 2021. The graph highlights another important factor determining mobility levels, i.e., peoples' adherence to the imposed policies and the government's ability to enforce them. In the beginning, mobility changes followed the changes in policy stringency in opposite directions. However, by the time mobility levels recovered to pre-pandemic levels at the end of 2020, this relationship became less linear. Therefore, to better understand mobility levels as a mechanism that drives labor market outcomes, it is important to also understand what drives policy adherence of citizens better in the respective setting. Many studies have looked at determinants of mobility restriction and COVID-19 guidelines.

However, most of them were either placed in developed countries[26-28] or lacked a representative sample size.[29-31] Given the importance of policy adherence to understand mobility levels, we complement our analysis by determining which factors were associated with respondents' self-reported mobility reduction in Kenya over the course of the pandemic.

We aim to add to the literature by examining labor market effects driven by changing mobility levels that can be attributed both to the measures imposed by the Kenyan government as well as people's adherence to these policies, combining data on policy restrictions with insights from Google Mobility Reports and large-scale household surveys. As far as we are aware, this is the first paper to investigate the causal effects of changing mobility levels on labor market outcomes over the course of the pandemic in a developing country. By estimating these causal effects, our findings inform both researchers aiming to establish direct links from mobility to labor market outcomes as well as policymakers looking to balance the trade-off between saving lives and containing the magnitude of socio-economic costs. In line with this, our analysis of factors associated with adherence to mobility restrictions adds important information on how to design, target and communicate mobility restrictions in Kenya more effectively in order to increase the restrictions' ability to slow the spread of the virus.

VI.2 Materials and Methods

Rapid Response Household Surveys

To conduct our analyses of the mobility-related labor market effects of the COVID-19 containment measures, we leveraged multiple sources of data. Central to our analyses, we used the Kenya COVID-19 Rapid Response Phone Household Surveys (RRPS) to measure the labor market effects of the pandemic on households on a county level for multiple survey waves between 2020 and 2021. The Kenya COVID-19 RRPS was structured as a five-wave bi-monthly panel survey that targeted nationals, refugees and stateless persons and has representative weights for national as well as county (admin-1) levels. Five rounds of the survey were completed between May 2020 and February 2021 (Figure 1). The sampling frame of telephone numbers was composed of two groups of households. The first was based on a randomly drawn subset of the 2015/16 Kenya Integrated Household Budget Survey (KIHBS) with 9,009 households which covered urban and rural areas and was designed to be representative of the population of Kenya using cell phones.[32] The household head or a knowledgeable person within the household was interviewed via Computer Assisted Personal Interviews (CAPI) and was asked to provide telephone numbers. Given that this sampling frame was five years old at the time of the first RRPS wave, an additional group was added by applying Random Digit Dialing (RDD). This method contacted households from a list of mobile phone numbers that was created using a random number generator from the 2020 Numbering Frame produced by the Kenya Communications Authority. The initial sampling frame consisted of 92,999,970 randomly ordered phone numbers assigned to three networks: Safaricom, Airtel, and Telkom. There was no stratification, and individuals regardless of their household head status, that were reached through the selected phone numbers were asked about the households they lived in. Households reached via RDD made up between 18.7% and 20.4% of our sample in the five survey waves (Supplement Table 1).

The questionnaire covered multiple topics, such as behavior in response to the COVID-19 pandemic and mobility, changes in employment, income, food security, subjective well-being, access to education and health services, knowledge of COVID-19 and mitigation measures as well as perceptions of the government's response and coping strategies. The questionnaire was translated into Swahili, Luo, Arabic, French, Kirundi, Luganda, Oromo, Somali, Kinyarwanda, Tigrinya, Nuer and Dinka to ensure all respondents could be interviewed in a language they were comfortable with. Our analysis focuses on working adults between 14 and 65 years old. We attained nationally representative RRPS data from 24,340 respondents. Out of these, 22,708 respondents gave complete information on employment status, 11,045/ 11,860 respondents on agricultural hours/income, 4,486/3,197 respondents on wage hours/income and 1,681 respondents on self-employment hours as well as the other covariates we consider. Sample characteristics were consistent across survey waves (Supplement Table 1). For the analyses of determinants of self-reported mobility reduction, we attained complete data from a total of 12,563 respondents**.**

Mobility Development

To determine changing mobility levels over the course of the pandemic, we used Google Community mobility reports.[33] These mobility reports provide insights into how mobility changed during the pandemic and into policies' effectiveness aimed at reducing mobility. Google mobility reports tracked aggregated, anonymized sets of GPS data for changes in mobility from users who opted-in/ did not opt out of location history for their Google account. The data shows how visits to (or time spent in) categorized places changed compared to a baseline. The baseline is the median value for the specific weekday from the 5-week period Jan 3 – Feb 6, 2020. Data was recorded for a total of six different location types, residential, grocery and pharma, transit, workplaces, retail and recreation and parks and leisure and collected on a county level (admin 1) as is our RRPS data. We considered five of them, excluding parks and leisure, as we wanted to focus on dimensions of social and economic life to construct the average mobility change.[34] The average mobility change was computed by taking the weekly overall average mobility change of the four location types (multiplying residential mobility change with minus one to attain a negative value for overall mobility reduction outside of home). This data was available for 37 out of 47 counties. The counties without mobility data were Elgeyo-Marakwet, Isiolo, Lamu, Mandera, Marsabit, Nyamira, Samburu, Tana River, Wajir and West Pokot.

Policy Stringency

To determine the degree of mobility restrictions in Kenya, we used the COVID-19 Government Response Tracker from the Blavatnik School of Government which tracked and collected systematic information on policy responses from governments during the pandemic for multiple countries.[35] The tracker traced health policies, economic policies and containment and closure policies of governments and assigned them an ordinal value ranging from 0 to 100 depending on severity and penetration across the country. We considered the latter type, i.e. containment and closure policies enacted by the Government of Kenya. Among the measures that were assigned ordinal values were school closures, workplace closures, cancellation of public events, restrictions on gatherings, closure of public transport, stay at home requirements, as well as restrictions on national and international travel. The index was calculated using these ordinal containment and closure policy indicators, plus an indicator recording public information campaigns (Hale et al. 2021). Data for Kenya was aggregated on a national level for each day starting January 1, 2020, ranging from 0 to 88.89. For our analyses, we calculated weekly average policy stringency levels to match the granularity of data of mobility and labor market outcomes.

Confirmed COVID-19 cases in Kenya

As part of our analyses, we also considered confirmed COVID-19 cases in Kenya, both national aggregates and county cases. National confirmed COVID-19 cases were obtained from both published government briefs as well as the data set on Policy Stringency, that also included national reported confirmed COVID-19 cases. For state-specific confirmed cases, we used regular updates by the Kenyan Ministry of Health from the respective homepage and Twitter.[36]

Climate data on average ground temperature and precipitation

Our analysis also included county-specific monthly climate data, i.e., monthly average ground temperature in degrees Celsius as well as monthly average precipitation in mm from Jan 2020-Dec 2021. This data was published by the Climate Research Unit (v4.06) and was available for 36 out of 37 counties, excluding Kajiado.[37] As such, we had complete data for 36 counties representing a total of 87.5% of the Kenyan population based on the 2019 KNBS census data. Monthly precipitation varied from 0.2 (Isiolo June 2020) to 408.9 mm/month (Trans-Nzoia July 2020), while monthly temperature averages ranged from 13.3 (Nyandarua July 2021) to 30.9 degrees Celsius (Turkana Oct 2020) during the time that the RRPS were conducted.

Labor Market Outcomes of Interest

Labor market outcomes from the RRPS could be allocated into three categories: A) employment status; B) hours worked in the past 7 days; C) income earned in the past 14 days per adult and thus combine both extensive margins of employment (category A) and intensive margins of employment (categories B and C). Within these categories, we looked at a total of 8 different labor market outcomes: 1) % employed, 2) % unemployed, 3) % not in the labor force, 4) hours worked in agriculture, 5) hours worked in wage employment, 6) hours worked in self-employment, 7) agricultural earnings and 8) wage earnings (Supplement Table 2). The wage indicators combined both formal and informal employment. We took weekly averages for all adults for which we have data available and aggregated them on a per county per-week level, which reflected the sampling and data collection strategy of the RRPS. County-specific weekly data points ranged from 1 to 51, with 75% of week averages containing more than 2- 6 observations per county depending on the labor market outcomes. For three of the eight variables, i.e., 4) hours in agriculture, 5) hours in wage employment, and 8) wage earnings, the RRPS survey also asked recall questions for levels prior to COVID-19 in February 2020. We included these recall responses as additional week averages in the last week of February, giving us additional pre-pandemic data points.

VI.3 Statistical Analyses and Estimation Strategy

Causal Impact of Mobility on Labor Market Outcomes

OLS Regression Results

We started our analysis by running OLS and county as well as month fixed effects regression for the average weekly mobility change and average weekly labor market outcomes in a simple model and a model including additional covariates averages of economic uncertainty, fear of illness, knowing someone who had an infection, the change in national confirmed COVID-19 cases compared to the previous week in %. All models yielded significant correlations between mobility levels for the extensive margins of employment and models (1) and (3) also for the number of hours worked both in formal and informal wage employment. Coefficients were similar for the extensive margins of employment, with a correlation coefficient of ~0.003 for outcome employed, implying that a 1 percent increase in mobility was associated with an increase in employment of 0.3 percentage points (Table 1). Including the set of additional covariates yielded significant results for both outcomes related to agriculture.

However, plain OLS regression results (including fixed effects regression) can hardly be interpreted as causal. At first, it is easy to find third variables that have explanatory power for both, such as overall levels of fear of economic and health consequences. Our surveys asked specifically for these sentiments of uncertainty and fears of health and economic consequences. Yet, even if we controlled for these sentiments, the main problem of reverse causality would remain, i.e., the fact that mobility does not only explain changes in labor market outcomes but that labor market outcomes and overall economic activity themselves have impacts on observed mobility. Therefore, the regression results in Table 1 cannot be considered causal in any direction.

Identification Strategy

To address these issues and given that mobility levels are highly interlinked with economic activity, we leveraged policy stringency as an exogenous shock in an IV estimation framework to overcome the issue of reverse causality and determine the causal impact of varying mobility levels on labor market outcomes in Kenya. As such, we used the overall policy stringency levels in Kenya as an instrument for observed mobility levels. We applied the following first-stage regression controlling for the relative change of confirmed national cases:

$$M_{tc} = PSI_t + X_{tc} + C_t + Clim_{mc} + \delta_{tc} + \omega_{tc}$$

Table VI.1: OLS and FE estimates results for labor market outcomes of interest using changing mobility levels as explaining variable in 36 Kenyan counties

	OLS (1)	OLS incl. covariates (2)	OLS incl. covariates & FEs (3)
Employment (% of Hh members)			
Employed	**0.004***** (0.00)	**0.003***** (0.00)	**0.003***** (0.00)
n	*1649*	*1511*	*1511*
Unemployed	**-0.001**** (0.00)	**-0.001***** (0.00)	**-0.001**** (0.00)
n	*1649*	*1511*	*1511*
Not in labor force	**-0.003***** (0.00)	**-0.002***** (0.00)	**-0.002***** (0.00)
n	*1649*	*1511*	*1511*
Hours Worked in past 7 days			
Agriculture	0.001 (0.02)	0.005 (0.02)	0.004 (0.03)
n	*1441*	*1406*	*1406*
Wage Job (formal and informal)	**0.064*** (0.03)	0.065 (0.03)	**0.120**** (0.04)
n	*1161*	*1124*	*1124*
Self-Employment	0.037 (0.04)	0.065 (0.04)	0.026 (0.06)
n	*780*	*761*	*761*
Income in past 14 days in KSH			
Agriculture	7.216 (6.44)	1.872 (6.87)	0.895 (7.65)
n	*1495*	*1453*	*1453*
Wage Job (formal and informal)	13.845 (10.49)	22.560 (12.59)	10.103 (15.51)
n	*1018*	*985*	*985*
# Counties	*36*	*36*	*36*

Note: Aggregated on weekly levels, *** is significant at the 1% level, ** is significant at the 5% level and *is significant at the 10% level, , equal weight of each county-week, FE: Including county and monthly fixed effects

M_{tc} refers to the average mobility change on a county level, PSI_t to the Policy Stringency Index on national level, and δ_{tc} denotes county as well as month-fixed effects. We included monthly fixed effects to control for seasonality in the Kenyan labor market. X_{tc} captures the county/week-specific averages of economic uncertainty, fear of illness, age and education levels of respondents. We included responses on concerns about the disease in terms of concerns about the illness itself, as well as fear of economic consequences to control for potential signaling effects of the implemented policies and to ensure the exclusion restriction holds. To control for the overall development of the pandemic, we also included changes in Kenya's weekly reported COVID-19 cases as well as answers to the questions whether a household knew of someone who had been infected with COVID-19. This latter control was added because reported cases were expected to be much lower than actual cases and therefore, nationally representative surveys asking about known cases may serve as an important addition to representing the overall course of a pandemic. C_{tc} refers to the % change in confirmed cases in week t compared to week t-1 on the national level. We incorporated the % change in confirmed cases to filter out "fear" effects that were not driven by public policy changes. $Clim_{mc}$ denotes county-specific monthly climate data, including average 2m ground temperature in degrees Celsius as well as precipitation in mm/month. We also considered county-level case changes, However, these did not prove significant at all, presumably due to the large uncertainty between reported vs. actual numbers.

The second stage of our analysis was a county and monthly fixed effects regression using county-week panel data:

$$Y_{tc} = \widehat{M}_{tc} + X_{tc} + C_t + Clim_{mc} + \delta_c + \varepsilon_{tc}$$

With Y_{tc} being our labor market outcomes of interest. For respondents that provided us with recall baselines, we assumed the education as well as the age to be the same at the time of the baseline, given that recall values were from February and survey data was available as of June of the same year. A full overview of the covariates can be found in Supplement Table 2. It is possible that the policies reducing mobility were enforced differently across counties and that institutional quality may have had an effect on people's adherence. While we were not able to attain county-specific data on institutional quality, research has shown that institutional quality has been related to crime levels.[38,39] We therefore sanity checked our results by running the same analyses using the interaction of Kenya's policy stringency index with county-specific crime index levels from 2019 as an instrument to allow for potential differences in the government's ability to enforce the mobility restrictions (Supplement Table 3).

Threats to Identification Strategy

Our identification strategy relies on two assumptions. At first, the exclusion restriction is that the reduction of mobility was the only channel through which the government's policies aimed at curbing the spread of the virus affected labor market outcomes. Clearly, this is only possible when we can control for any signaling effect and concerns that the imposed policies may have had on households. As part of the RRPS survey data, we had representative data on fear of the illness as well as self-perceived economic uncertainty, which allowed us to control for these sentiments. Additionally, our estimation strategy relies on the assumption that the IV is exogenous, i.e., that there is no causal impact running from labor market outcomes to our instrument, the policy stringency index itself. There are a couple of observations that we believe justify this assumption. At first, the Kenyan government immediately implemented very strong measures, including a national curfew at a time when only a handful of COVID-19 cases had been confirmed in the country. Secondly, the government quickly enacted several economic relief policies, which can be taken as anecdotal evidence that the mobility policy's primary concern was to curb the spread of the virus (see Presidential Announcement from April 16th, 2020) and economic considerations were tried to be addressed otherwise. We investigated this idea by looking at survey responses for questions on whether households had received transfers from the government or politicians, including the amounts. The share of people self-reporting receiving transfers from government programs ranged from 1.3% in wave 4 to 4.1% in wave 5, yet with no clear patterns across the waves. However, looking at the magnitude of transfers compared to pre-pandemic levels, there is anecdotal evidence of increases in all survey waves (n=381) compared to pre-pandemic levels, with increases ranging from an additional 913 KSH on average in wave 2 to 2,120 KSH in wave 4. Additionally, we looked at the development of people's trust in the government's ability to deal with the pandemic as a proxy for public sentiment about the government's performance that could reflect increasing pressure on politicians to give economic consequences more priority. Indeed, average scores changed from 1.51 during wave 1 of the RRPS to 1.40 during wave 5. However, given that trust levels were high on average (distrust was coded as 0, neutral as 1 and trust as 2), we do not believe this change to have made much of a difference. Overall, it does not seem that more severe labor market conditions were associated with increased political pressure, enabling the Government of Kenya to form mobility policies that were solely aimed at saving lives and containing the spread of the virus. Finally, to sanity check this assumption, we reran the analyses by using the policy stringency index levels of Kenya's neighboring countries, for which we believe economic concerns within Kenya played little to no role.

Factors Associated with Self-Reported Mobility Restrictions

Our second set of analyses looked at whether households self-reported any behavioral change that could be attributed to self-restricting mobility and interaction. The outcome variable was a binary variable "Any self-reported mobility restriction" that was given a value of 1 if respondents stated that due to COVID-19, they had either avoided groups more often, stayed at home more, traveled outside less, gone to work less, or returned home earlier at night (Supplement Table 3).

Looking at factors that are associated with any self-reported mobility restriction, we – as above – considered the number of confirmed COVID-19 cases and the overall policy stringency. In addition, we incorporated a set of 10 covariates recorded in the RRPS. The covariates included respondents' answers to questions about their trust in the government in handling the pandemic, trust in their fellow citizens, characteristics such as sex, education level, age, employment status, location (urban vs. rural) and household heads status and whether they know someone who was infected or whether they were worried about having enough food (Supplement Table 4). To determine factors that influenced any self-reported mobility-reducing behavior, we ran a multilevel logit model at the household level, in which week and county formed our two levels of analysis:

$$m_{it} = x_{it} + PSI_t + C_t + \vartheta_{it},$$

With m_{it} being self-reported mobility for household i in week t, x_{it} household characteristics, C_t the % change in confirmed cases for week t compared to t-1 and ϑ_{it} the error term.

VI.4 Results

Causal Impact of Mobility on Labor Market Outcomes

Policy stringency on a national level and average mobility change in the individual counties were significantly and negatively associated with one another. Table 2 shows the results of our first-stage regression, which was significant not just for policy stringency but also negatively and statistically significantly related to the weekly change of national confirmed COVID-19 cases. We see that in terms of magnitude however, a one-point Policy Stringency Index increase was associated with a roughly seven times decrease in mobility compared to a percentage point increase in national weekly confirmed COVID-19 cases. At the same time, overall mobility was negatively associated with increasing temperature and positively associated with precipitation, however, with a small coefficient. Our F statistic of 45.4 confirmed that the policy stringency index indeed appears to be a valid instrument for changing mobility levels.

Table VI.2: First Stage Regression Results

Weekly Mobility Change Levels during survey waves I-V (May 20-July 21), n=1,551	Coefficient (S.E.)	95% Confidence Interval
Policy Stringency Index	**-0.463***** (0.048)	[-0.557; - 0.368]
Weekly Change Confirmed COVID-19 cases (national) in %	**-0.070***** (0.013)	[-0.096; -0.044]
F-Statistic		45.40

Note: Aggregated on weekly levels, *** is significant at the 1% level, equal weight of each county-week

There was a significant impact of changing mobility on the overall employment and labor force participation of household members (Table 3). We found positive effects of increasing mobility on employment and unemployment and negative effects on not being in the labor force. A 10% increase in mobility caused a ~6.5 percentage points of people to return to the workforce, and a ~8 percentage points increase in employment. Roughly two-thirds of people entering employment due to increasing mobility levels re-joined the labor force, while the remaining third re-entered from unemployment. Hence, we see that the mobility restrictions had a strong effect on people's employment, mainly through re-entering the labor force. Given that our RRPS data commenced in May 2020 at a time when mobility recovery was already underway, this can be interpreted as increased mobility signaling to people that things were returning back to normal, which caused them to look for jobs again. The results were consistent across urban and rural areas.

Table VI.3: IV estimation results for labor market outcomes of interest using changing mobility levels as explaining variable in 35 Kenyan counties

	OLS incl. covariates & FEs (3)	IV- full sample (4)	IV- rural (5)	IV-urban (6)
Employment (% of Hh members)				
Employed	**0.003***** (0.00)	**0.008***** (0.00)	**0.007***** (0.00)	**0.008***** (0.00)
n	*1511*	*1511*	*1428*	*1425*
Unemployed	**-0.001**** (0.00)	**-0.003***** (0.00)	**-0.002*** (0.00)	**-0.001** (0.00)
n	*1511*	*1511*	*1428*	*1425*
Not in labor force	**-0.002***** (0.00)	**-0.007***** (0.00)	**-0.006***** (0.00)	**-0.007***** (0.00)
n	*1511*	*1511*	*1428*	*1425*
Hours Worked in past 7 days				
Agriculture	0.004 (0.03)	0.089* (0.04)	0.028 (0.05)	**0.153**** (0.05)
n	*1406*	*1406*	*1261*	*1208*
Wage Job (formal and informal)	**0.120**** (0.04)	**0.567***** (0.15)	**0.421*** (0.17)	**0.606***** (0.15)
n	*1124*	*1124*	*700*	*883*
Self-Employment	0.026 (0.06)	0.126 (0.11)	0.011 (0.17)	0.072 (0.18)
n	*761*	*761*	*393*	*554*
Income in past 14 days in KSH				
Agriculture	0.895 (7.65)	10.885 (42.73)	13.613 (69.73)	17.178 (43.02)
n	*1453*	*1453*	*1314*	*1267*
Wage Job (formal and informal)	10.103 (15.51)	33.537 (63.77)	-13.220 (78.58)	57.011 (83.71)
n	*985*	*985*	*575*	*737*
Incl. county and monthly FEs	*Yes*	*Yes*	*Yes*	*Yes*

Note: Aggregated on weekly levels, *** is significant at the 1% level, ** is significant at the 5% level and *is significant at the 10% level, equal weight for each county-week

Looking at the intensive margins of employment, i.e. the indicators that provide context about existing employment, we found that the most significant effects were for hours worked by household members in wage employment (formal and informal). Here, a 10% increase in mobility was associated with an increase of ~6 wage hours per week. Hours worked in agriculture were significant at a 10% level for the whole sample. However, results were driven by urban areas with higher statistical significance. For income generated from wage work and agriculture, we found no statistically significant effects of recovering mobility. Comparing urban vs. rural, we found that effects on the extensive margins of employment were similar, while the effect on hours worked in wage employment and agriculture were larger in urban settings. Finally, the estimated coefficients using our IV approach yielded much higher coefficients compared to our previous OLS estimates that were subject to reverse causality.

Looking at the other correlates that we included in our analyses (Table 4), we found that most of our controls did not show statistical significance. Next to changing mobility levels instrumented for by the policy stringency index, age and education were consistently associated with our labor market outcomes. Education was positively associated with employment and wage income while negatively associated with the number of wage hours worked. Age was also positively associated with employment, indicating that the overall labor market recovery was more pronounced for older, more experienced and educated workers.

Table VI.4: IV estimation results for whole set of covariates used in regression model in 36 Kenyan counties

(4) IV- full sample	Employed	Unemployed	Not in Labor Force	Agri Hours (7 days)	Wage Hours (7 days)	Self-employment Hours (7 days)	Agri Income (14 days)	Wage Income (14 days)
IV Mobility	**0.008*** **	**-0.003*** **	**-0.007*** **	0.089*	**0.567*** **	0.126	10.885	33.537
Economic Uncertainty	0.004	0.014	-0.010	1.987	1.940	-3.057	1189.079	1198.950
Fear of Illness	0.020	-0.042*	-0.001	2.416*	3.423	6.234	-569.311	1105.543
Know s/o Infected	-0.044	-0.017	0.103	0.733	-8.314	7.378	40.944	-1763.736
Age	**0.010*** **	-0.001*	-0.000	-0.025	-0.123	-0.026	0.879	57.183*
Education	**0.031*** **	**0.014** **	**0.017** **	-0.458	**-1.340** **	0.206	159.852	**2228.515*** **

Note: Aggregated on weekly levels, * is significant on 10% level, ** significant on 5% level, ***significant on 1% level, equal weight of each county-week

It is possible that mobility's impact and the mechanisms through which it impacted labor market outcomes varied at different stages of the pandemic. For this reason, we also compared results for different stages, i.e. we split our sample into a "initial recovery" and "post-recovery sample", the first reflecting waves 1 to 3, in which mobility returned to pre-pandemic levels and a post-recovery phase, in which mobility exceeded pre-pandemic levels (Table 5). Our results show first that the effects on extrinsic margins of employment differed quite substantially between the two phases. Re-entering the labor force, in the beginning, led to re-employment as well as higher unemployment, while between waves 4-5, recovering mobility levels led employment to increase similarly from people re-entering the workforce and people leaving unemployment. Likewise, for the intrinsic margins of employment, hours worked were positively affected for all employment types during the recovery phase, while income generated was significant for agricultural income in the past-recovery phase. Looking at urban and rural separately, we found that employment recovery was driven more by rural areas, particularly during the initial recovery phase. Recovery of hours worked in wage employment was more pronounced during the initial recovery phase, while recovery of agricultural hours worked was more pronounced over the course of the post-recovery phase in rural settings and consistent across both phases in urban areas.

To sanity check our results, we reran analyses from Table VI.3 using, firstly, county-specific crime index levels from 2019 that we interacted with policy stringency levels. We also reran results using the average stringency index levels of Kenya's neighbors as well as a combination of both by interacting county-specific crime index with the average stringency index of Kenya's neighbors (Supplement Table 5). Results for these sanity checks were similar, with slightly higher effects for the extensive margins of employment as well as larger and more statistically significant results for hours worked in agriculture for the models using Kenya's neighboring countries' average stringency levels. All in all, however, our results were confirmed, i.e., that extensive margins of employment were most affected and that among the intensive margins of employment, primarily hours worked in wage employment and, to a lesser degree, hours worked in agriculture were affected. Hours worked in self-employment and income generated were not affected by recovering mobility levels in any of the specified models. As a final sanity check, we used different weekly lags of explaining variables, given that low mobility levels may take a bit of time to translate into labor market outcomes. However, we did not find this to impact our results.

Table VI.5: IV estimation results for our outcomes of interest for different stages of the pandemic in 36 Kenyan counties

Wave 1-3 (initial recovery) Wave 4-5 (post-recovery)	National Wave 1-3 (1)	National Wave 4-5 (2)	Rural Wave 1-3 (3)	Rural Wave 4-5 (4)	Urban Wave 1-3 (5)	Urban Wave 4-5 (6)
Employment (% of Hh members)						
Employed	**0.008**** (0.00)	**0.013***** (0.00)	**0.009***** (0.00)	**0.010***** (0.00)	**0.004***** (0.00)	**0.008***** (0.00)
n	*764*	*747*	*718*	*710*	*716*	*709*
Unemployed	**0.003**** (0.00)	**-0.006***** (0.00)	**0.002***** (0.00)	**-0.004*** (0.00)	**0.008***** (0.00)	**-0.007***** (0.00)
n	*764*	*747*	*718*	*710*	*716*	*709*
Not in labor force	**-0.010***** (0.00)	**-0.007**** (0.00)	**-0.011***** (0.01)	**-0.007***** (0.00)	**-0.011***** (0.00)	**-0.001***** (0.00)
n	*764*	*747*	*718*	*710*	*716*	*709*
Hours Worked in past 7 days						
Agriculture	**0.269**** (0.09)	**0.295***** (0.09)	0.075 (0.10)	**0.387***** (0.11)	**0.440***** (0.10)	**0.319**** (0.10)
n	*706*	*700*	*623*	*637*	*589*	*619*
Wage Job (formal and informal)	**1.273***** (0.30)	**-0.516*** (0.22)	**1.400**** (0.48)	-0.688* (0.30)	**1.074***** (0.27)	-0.522 (0.32)
n	*495*	*665*	*254*	*481*	*370*	*549*
Self-Employment	**0.542**** (0.18)	0.075 (0.14)	0.239 (0.33)	-0.046 (0.36)	0.481* (0.20)	0.414 (0.32)
n	*406*	*355*	*188*	*200*	*306*	*247*
Income in past 14 days in KSH						
Agriculture	-95.430 (76.73)	**-241.248**** (89.14)	-132.051 (142.79)	-108.765* (49.19)	-2.963 (70.65)	-314.380* (124.50)
n	*748*	*741*	*671*	*679*	*639*	*664*
Wage Job (formal and informal)	181.906 (116.60)	-1.124 (106.74)	-141.147 (171.29)	-46.355 (153.79)	158.664 (155.39)	-59.723 (132.63)
n	*403*	*618*	*196*	*413*	*284*	*488*

Note: Aggregated on weekly levels, * is significant on 10% level, ** significant on 5% level, ***significant on 1% level, equal weight of each county-week

Factors Associated with Self-Reported Mobility Restrictions

Among the broad set of potential determinants influencing self-reported mobility reduction, we found that trust in the government handling the pandemic well, trust in fellow citizens, knowing someone who had been infected, the overall policy stringency level and monthly average temperature and precipitation were statistically significant (Table 6). Interestingly, both the trust in the government's ability to handle the pandemic as well as knowing someone who had been infected had a negative sign, implying either that good trust in the government's ability to deal with the pandemic reduced the individual households' need to comply with recommended mobility restrictions or that having someone infected in rural areas implied increased need of support which translates into mobility. Overall, however, it seems that one of the main drivers of self-reported mobility reduction was the overall severity of the mobility restriction policy in Kenya.

Table VI.6: Determinants of self-reported mobility restricting behavior in 46 Kenyan counties

Self-reported mobility restriction	National	Rural	Urban
	n=11,106	n=5,213	n=5,870
Trust in Government	**-0.43*** **	-0.23	**-0.33** **
Trust in fellow citizens	**0.62** **	**0.98*** **	0.28
Sex (Female)	-0.15	-0.09	-0.40
Education Level	-0.07	0.08	**-0.23*** **
Household Head	0.03	-0.17	0.09
Age	-0.00	0.01	**-0.02** **
Urban/Rural	0.06	N/A	N/A
Know someone who is/was infected	**-0.95** **	**-1.52*** **	-0.38
Employed	**0.46***	0.54	-0.11
Worried about food	0.30	**0.58** **	0.12
Policy Stringency Index	**0.07*** **	**0.07*** **	**0.07*** **
Weekly Change COVID-19 cases (%)	0.00	-0.00	0.00
Monthly 2m Ground Temperature in °C	**0.36***	**0.45***	0.31
Monthly Precipitation in mm	**-0.01*** **	**-0.00** **	**-0.01*** **

Note: *** is significant at the 1% level, ** is significant at the 5% level, * is significant at the 10% level, equal weights of each survey wave; given we do not use mobility data here, our sample comprises 46 counties that have climate as well as RRPS survey data

Given that policy stringency is a continuous variable running from 0-100, a five-point increase in the stringency index had an effect size that offset the negative effect of trusting in the government's ability to handle the pandemic. Comparing urban vs. rural outcomes, the statistically significant results for the whole sample were driven by either urban or rural residents apart for policy stringency and precipitation, which showed statistical significance in all areas. While in rural areas, self-reported mobility reduction was associated with trust in fellow citizens, worrying about food, and knowing someone who was infected, in urban areas, education levels, age and trust in the government's ability to handle the pandemic were significantly associated with self-reported mobility restricting behavior.

VI.5 Discussion

Our study has a number of salient findings. First, recovering mobility levels in Kenya following the initial declines in early 2020 caused people to (re-) enter employment, two-thirds of the effect coming from people re-entering the labor force. Second, while increased mobility caused an increase in hours worked in wage employment (formal and informal), no consistent significant effects could be found for generated incomes. Potential reasons for this observation may be that employers continued to support workers for a while up until their re-entry or otherwise lowered payments at the beginning of the pandemic and did not increase the payment as the number of hours worked went up again either due to financial distress or with the promise of later repayment. We allowed ourselves a cautious interpretation by leveraging asset information for a total of seven assets (radio, mattress, charcoal jiko, refrigerator, television, landline telephone and computer/tablet/laptop) that became available during waves 4 and 5 of the RRPS surveys for a total of 10,785 households, which also incorporated baseline values from February 2020. Comparing wave averages to pre-pandemic levels showed that overall asset ownership reduced over the course of the pandemic until wave 4 and wave 5, with a slight recovery between wave 4 and wave 5. These results were consistent when incorporating the complete set and sub-sets of the seven assets. We interpret this as evidence that households had to sell certain assets to cope with income and job loss as well as health-related expenses, which makes the idea that employers continued payments or that social safety nets were at play rather implausible. However, given that we lacked precise income baseline data, understanding the exact dynamics over the entire course of the pandemic will be a subject for future research. Comparing urban vs. rural, we did find additional statistically significant effects of mobility on hours worked in agriculture in urban households, which could be explained by agricultural workplaces in the rural setting often being directly linked to the place of living i.e., farms or plantations connected with villages.

Additionally, looking at different stages of the pandemic, we found that different mechanisms were at play at different times during the pandemic. Particularly in rural settings, people quickly re-entered employment already during the pre-recovery phase, while in urban areas, people mostly entered unemployment. During the post-recovery phase, however, people in urban areas left unemployment more than re-entering the labor force compared to rural areas. This implies that the labor markets in rural areas were faster to ramp up employment with increased mobility than labor markets in urban areas. Thinking about safety nets and mitigation measures, knowledge about differential impacts across sectors in urban and rural areas is important to identify target groups and quantify the economic costs of restriction measures in these specific areas. To determine the causal effects of mobility not just during a recovery phase but for overall economic and labor market activity, future research will rely on researchers' ability to attain high-frequency data covering not only the course of a pandemic but also the time of the outbreak. Furthermore, given that our study is a country-specific case, it will be interesting to see how estimates of the causal impact of mobility on economic recovery compare to findings from other countries or regions.

Finally, we found that people's trust in the Kenyan government's ability to deal with the pandemic, trust in fellow citizens, knowing someone who has been infected, overall level of policy stringency and climate significantly influenced people's self-reported reductions of mobility. There were differences between urban and rural households. While for rural households, the worry about food, knowing someone who was infected, trust in fellow citizens and temperature were of significance, in the urban setting, other factors were relevant such as education, age and trust in the government's ability to handle the pandemic. This could be linked to urban households being more educated and having higher opportunity costs to self-reduce mobility, as well as the fact that governments tend to be more present and visible in urban areas compared to rural areas. At the same time, the significant negative coefficient of knowing someone who has been infected in rural households could point towards the need to support the person that falls ill requiring additional mobility. This increased relevance of social ties (as opposed to looking at the government) is also backed by the relevance of people's trust in their fellow citizens in the rural setting. We are aware that self-reported behavior data needs to be treated with caution.[40] We nevertheless believe that our large sample allows for important insights into determinants of self-restricting behavior during the pandemic. Comparing coefficients, a 15-point increase in policy stringency outweighed most of the other coefficients, highlighting potential signaling or enforcement of rules that came with more severe government measures. Our results underscore the importance of strong government measures and communication to save lives. However, they also show that different messages and different channels need to be applied to convince citizens to self-reduce mobility and social interaction.

Our study has a few limitations that are primarily due to data availability. At first, given that the RRPS started in May, we lack baseline data for pre-pandemic levels. While for three of the five labor market outcomes, we did have retrospective recall values, this data is subject to the bias that recall data carries. The interpretation thus needs to be taken cautiously as the causal effect of mobility recovery may differ from the causal effect of mobility on labor market outcomes in non-pandemic times. Another limitation is the fact that we did not have county-level stringency index data but had to rely on national aggregates to instrument for county-specific mobility changes. However, given that a) only very few policies were implemented on county levels and b) the national index score is an average of stringency across the country, we believe that this is justifiable. Furthermore, interacting national levels with local crime indices yielded similar results. Due to the nature of the RRPS survey waves and the fact that interviews had to be conducted via phone, there is a potential bias coming from the selection at baseline and the attrition of the selected population in the follow-up waves. Phone surveys can only reach respondents using a phone in an area with network coverage. Therefore, statistics are only representative for this part of the population, potentially excluding the poorest households that do not own phones or live-in areas with no network coverage. RRPS weights were adjusted by the World Bank in a two-step approach to make sure the RRPS is as representative as possible for the entire population and to adjust for attrition.[41] We therefore do not believe this bias to be relevant. Another data limitation came from the fact that we were only able to attain mobility data for 37 counties, and out of these attained climate data for 36. The missing counties do not show a specific pattern in terms of geography, size or wealth and given that the counties in our sample represent 87.5% of the Kenyan population, we still consider our results to be representative. Also, this is only relevant for our IV estimation, as the analysis of correlates of self-reported mobility does not rely on Google mobility data. Finally, we included county-specific monthly temperature data however, our level of observation was country-specific weekly values. We realize that our results would be more precise if we had the additional variation of weekly climate data, however unfortunately, we did not find them to be publicly available.

VI.6 Conclusion

We examined the impact of increasing mobility on household labor market outcomes over the course of the COVID-19 pandemic in Kenya between March and April 2020 and determined which factors influenced people's self-reported adherence to imposed mobility-restricting policies.

From May 2020 until June 2021, a rise of 10% mobility led to an increase of 8 percentage points in household members being employed. At the same time, 10% of recovering mobility caused an increase of 5.7 wage hours per week (formal and informal). The results for extrinsic margins of employment were similar for urban and rural, with differences regarding the timing of the labor recovery. Looking at the intrinsic margins of employment, hours worked were overall more affected in urban areas, again with differences regarding the timing of the recoveries. Income however, did not seem to be causally influenced by recovering mobility. Among the factors influencing self-reported mobility and, thus, nationwide mobility levels, trust (in the government and fellow citizens), knowing someone who has been infected, country-wide policy stringency levels and monthly climate were statistically significant, policy stringency levels being particularly relevant.

Knowing about the sectors affected most by mobility levels as well as the stage at which this affect takes place, is important knowledge for policymakers. Policymakers in future health crises will need to carefully evaluate policies aimed at reducing mobility with the economic costs that are associated with them. Finally, providing safety nets and working to save employment status in formal and informal wage employment will continue to be important measures to shield people from the most severe consequences of the pandemic.

VI.7 Appendix

Supplement Table VI.1 Sociodemographic comparison of different RRPS waves

	Wave 1 (14/5/2020-8/7/2020)	Wave 2 (16/7/2020-18/9/2020)	Wave 3 (28/9/2020-30/11/2020)	Wave 4 (15/1/2021-25/3/2021)	Wave 5 (29/3/2021-25/6/2021)
Average Age of Respondent	35.03	35.19	34.71	36.1	36.22
Share of Female Respondents	50%	53%	51%	50%	49%
Average Education of Respondent*	3.29	3.31	3.39	3.25	3.31
Household size	4.13	4.15	3.4	3.65	3.26
Average Age of Household Head	39.53	40.08	37.42	37.7	37.67
Share of Female Household Heads	33%	36%	37%	41%	39%
Share Urban	35.9%	36.0%	37.0%	36.4%	40.0%
Sample Size	4,062	4,504	4,993	4,906	5,874
Share RDD	18.9%	18.7%	20.2%	17.2%	19.8%
Response Rate	36%	41%	45%	43%	51%

*An education level of 3 equals to completed post-primary, vocational, a score of 4 equals completed secondary education

Supplement Table VI.2: Variables for causal effect of mobility on labor market outcomes analysis

Role in Analyses	Category	Variables	Coding	Pre-COVID-19 Baseline
Outcome Variables	Employment Status	1. Respondent Employed (%)	Binary (Yes/No)	
		2. Respondent Unemployed (%)	Binary (Yes/No)	
		3. Respondent Not in Labor Force (%)	Binary (Yes/No)	
	Hours worked	4. Working Hours in Agriculture per Working Household Member in past 7 days	Ordinal	Yes
		5. Working Hours in Wage Employment per Working Household Member in past 7 days	Ordinal	Yes
		6. Working Hours in Self Employment per Working Household Member in past 7 days	Ordinal	Yes
	Income earned	7. Agricultural Earnings (KSH past 14 days)	Ordinal	Yes
		8. Wage Earnings (KSH past 14 days)	Ordinal	Yes
Explaining Variables	Fear of Illness	Yes to the question "Are you feeling nervous or anxious due to the coronavirus outbreak?" and statement of one of the following reasons: - Fear of myself or family getting infected by coronavirus - Fear of myself or family dying due to coronavirus - Fear of me infecting others in the community - Fear of losing access to health facilities	Binary (Yes/No)	N/A
	Economic Uncertainty	Yes to the question "Are you feeling nervous or anxious due to the coronavirus outbreak?" and statement of one of the following reasons: - Loss of employment / business - Fear of being unable to feed or provide for family - Effect on education system and school closures - Economic Crisis/Paralyzed Movement - Uncertainty of when lockdown will end / things will return to normal	Binary (Yes/No)	N/A
	Know s/o Infected	Do you know anyone that has, or has had, COVID-19/coronavirus?	Binary (Yes/No)	N/A

Supplement Table VI.3: Crime Index Levels in 2019 for 47 Kenyan counties

S/NO.	COUNTIES	POPULATION	CRIME	CRIME INDEX
1	Meru	1545714	6077	393
2	Muranga	1056640	3284	311
3	Embu	608599	1819	299
4	Kirinyaga	610411	1762	289
5	Kisii	1266860	3552	280
6	Mombasa	1208333	3374	279
7	Nyandarua	638289	1768	277
8	Tharaka Nithi	393177	1077	274
9	Kiambu	2417735	6597	273
10	Nyeri	759164	2002	264
11	Taita Taveta	340671	860	252
12	Nyamaria	605576	1523	251
13	Trans Nzoia	990341	2388	241
14	Lamu	143920	339	236
15	Nandi	885711	2066	233
16	Machakos	1421932	3314	233
17	Isiolo	268002	619	231
18	Laikipia	518560	1163	224
19	Nakuru	2162202	4730	219
20	Makueni	987653	2037	206
21	Uasin Gishu	1163186	2376	204
22	Kericho	901777	1819	202
23	Busia	893681	1789	200
24	Kitui	1136187	2190	193
25	Kisumu	1155574	2188	189
26	Nairobi	4397073	8246	188
27	Vihiga	590013	1024	174
28	Marsabit	459785	783	170
29	Bungoma	1670570	2811	168
30	Tana River	315943	529	167
31	Kilifi	1453787	2394	165
32	Bomet	875689	1433	164
33	Siaya	993183	1583	159
34	Homa Bay	1131950	1803	159
35	Kajiado	1117840	1678	150
36	Kakamega	1867579	2621	140
37	Elgeyo Marakwet	454480	633	139
38	Baringo	666763	836	125
39	Kwale	866820	1060	122
40	Migori	1116436	1323	119
41	Samburu	310327	363	117
42	West Pokot	621241	562	90
43	Turkana	926976	733	79
44	Narok	1157873	849	73
45	Garrissa	841353	488	58
46	Wajir	781263	356	46
47	Mandera	867457	363	42
	TOTAL	**47564296**	**93184**	**428**

*Source: The National Police Service (NPS): Annual Report 2019

Supplement Table VI.4: Variables for analysis of determinants of self-reported mobility reduction behavior

Role in Analyses	Category	Explanation	Coding
Outcome Variables	Self-reported behavior change	Any self-restricted mobility behavior (at least one answer with yes to the following questions): - Avoid groups more often? - Stay at home more? - Travel outside less? - Go to work less? - Return home earlier at night?	Binary (Yes/No)
Explaining Variables	Trust in Government	The Government is trustworthy in the way it manages the Coronavirus crisis?	Binary (Yes/No)
	Trust in fellow citizens	Generally speaking, would you say that most people can be trusted?	Binary (Yes/No)
	Sex (Female)	Gender Dummy	Binary (Male)
	Education Level	No education=0, University postgraduate=8	Ordinary
	Household Head	Household Head Status Dummy	Binary (Yes, No)
	Age		Ordinary
	Urban/Rural	Urban Dummy	Binary
	Know s/o infected	Do you know anyone that has, or has had, COVID-19/coronavirus?	Binary
	Employed	Employment Dummy	Binary
	Worried about food	Household missing/cutting meals in past 7 days (%) (at least one yes answer to the following 2 questions): - In the past 7 DAYS, how many days have ADULTS in your household skipped meals or cut the number of meals?	Binary

Supplement Table VI.5: IV estimation results for labor market outcomes of interest using changing mobility levels as explaining variable in 35 Kenyan counties

	IV- full sample (4)	Crime Index Adj. (5)	Neighbor Stringency (6)	Crime Adj. + Neighbor Stringency (7)
Employment (% of Hh members)				
Employed	**0.008***** (0.00)	**0.009***** (0.00)	**0.009***** (0.00)	**0.010***** (0.00)
n	*1511*	*1511*	*1511*	*1511*
Unemployed	**-0.003***** (0.00)	**-0.004***** (0.00)	**-0.003*** (0.00)	**-0.004*** (0.00)
n	*1511*	*1511*	*1511*	*1511*
Not in labor force	**-0.007***** (0.00)	**-0.006***** (0.00)	**-0.007***** (0.00)	**-0.008***** (0.00)
n	*1511*	*1511*	*1511*	*1511*
Hours Worked in past 7 days				
Agriculture	0.089* (0.04)	0.086 (0.05)	**0.139***** (0.04)	**0.176***** (0.05)
n	*1406*	*1406*	*1406*	*1406*
Wage Job (formal and informal)	**0.567***** (0.15)	**0.605**** (0.19)	**0.504***** (0.09)	**0.548***** (0.12)
n	*1124*	*1124*	*1124*	*1124*
Self-Employment	0.126 (0.11)	0.088 (0.18)	0.088 (0.12)	0.076 (0.15)
n	*761*	*761*	*761*	*761*
Income in past 14 days in KSH				
Agriculture	10.885 (42.73)	21.516 (56.44)	-6.478 (28.97)	-6.564 (36.89)
n	*1453*	*1453*	*1453*	*1453*
Wage Job (formal and informal)	33.537 (63.77)	34.536 (79.48)	49.263 (38.62)	72.501 (46.76)
n	*985*	*985*	*985*	*985*
Incl. county and monthly FEs	*Yes*	*Yes*	*Yes*	*Yes*

Note: Aggregated on weekly levels, *** is significant at the 1% level, ** is significant at the 5% level and *is significant at the 10% level, equal weight of each county-week

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Declaration

Declaration of author's contribution

Essay 1: Joint work with Rockli Kim (RK), Sebastian Vollmer (SV) and S.V. Subramanian (SS)

MH and RK had full access to all of the data in the study and take responsibility for the integrity of the data and the accuracy of the data analysis. SVS, RK, MH and SV conceptualized and designed the study. MH led data acquisition and analysis. MH, SVS, SV and RK contributed to data interpretation. MH led the writing, and SVS, RK and SV provided critical revisions to the manuscript. SV and SVS provided overall supervision.

Essay 2: Joint work with Rockli Kim (RK), Smriti Scharma (SS) Sebastian Vollmer (SV) and S.V. Subramanian (SVS)

SVS, RK, MH and SV conceptualized and designed the study. MH led data acquisition and analysis. MH, SVS, SV, SS and RK contributed to data interpretation. MH led the writing, and SVS, RK, SS and SV provided critical revisions to the manuscript. SV and SVS provided overall supervision.

Essay 3: *Joint work with Sebastian Vollmer (SV)*

SV and MH conceptualized and designed the study. MH led data acquisition and analysis. SV contributed to data interpretation. MH led the writing and SV provided critical revisions to the manuscript. SV provided overall supervision.

Essay 4: *Joint work with Nicolas Büttner (NB), Jan-Walter De Neve (JDN), Sebastian Vollmer (SV) and Kenneth Harttgen (KH)*

MH, KH and NB designed the overall concept of the study. MH acquired the data and conducted the statistical analysis and interpretation of data with NB. NB drafted the manuscript which KH, MH, JDN and SV critically revised for important intellectual content. Overall supervision was done by KH.

Essay 5: Joint work with Moritz Schreckenberger (MS) and Utz Paper (UP)

MH and UP conceptualized the research and designed the study. MH, UP and MS obtained and processed the data. MH conducted the statistical analysis and both MH and UP drafted the manuscript. Further supervision was provided by UP.