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Effects of the COVID-19 crisis on household food consumption and child nutrition in Mozambique

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Abstract: This study investigates the short-term impacts of an aggregate socioeconomic shock on household food consumption and children's nutrition using the case of the COVID-19 pandemic in Mozambique. In response to the economic downturn, households are expected to adjust their food choices both in terms of quality, towards cheaper and unhealthier food, and quantity, reducing diet diversification and increasing the exposure to malnutrition, mainly for children. Empirical evidence on such immediate effects is still scarce, mainly due to a lack of data. This paper aims to fill the evidence gap by relying on household survey data from 2019–20, which includes a detailed consumption module and anthropometric measures for children under five. We use a repeated cross-sectional econometric analysis to look at the variation in household food consumption and child nutrition before and after the pandemic. The results show that there has been a significant reduction in household food consumption and per capita caloric intake and an increase in stunting, especially among newborn children.

Key words: COVID-19, food consumption, nutrition, Mozambique

JEL classification: C21, D12, O12

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1 Introduction

Aggregate shocks, namely shocks that affect all individuals and all sectors of an economy (Foerster et al. 2011), have proven to have significant consequences on food consumption and nutrition (Bakhtiar and Rabbani 2021; Block et al. 2004; Ferreira and Schady 2009; Kavallari et al. 2014). The COVID-19 crisis presents some peculiarities that make it different from the previous aggregate shocks experienced by the global economy (Schmidhuber and Qiao 2020). Indeed, the COVID-19 crisis can be defined as a typical Keynesian supply shock (Guerrieri et al. 2020), which involves two recessive shocks simultaneously: a demand shock superimposed on a supply shock (Charles et al. 2021). Additionally, while previous crises mainly affected some countries rather than others, as happened during the 2007–08 financial crisis, COVID-19 was a truly global crisis (Schmidhuber and Qiao 2020). Given the globalized economy, characterized by multiple, interlinked value chains and incomplete markets, each country has been affected by the package of restrictions implemented at the national level but also indirectly by the restrictions on international trade and the global value chains. As a result, not only high-income countries but also low- and middle-income countries suffered from the negative effects of the COVID-19 crisis. In many developing economies, the crisis exacerbated an already fragile situation where severe structural problems and other concurrent shocks, such as extreme weather events and conflicts, had led to food insecurity and malnutrition among the population. Mozambique is not an exception. The global economic downturn, in combination with a series of government restrictions, negatively affected employment, income, and consumption (Barletta et al. 2022; Betho et al. 2022). In this paper we will assess whether these restrictions and their negative consequences translated into higher exposure to food insecurity and malnutrition.

COVID-19 can increase malnutrition in different ways: through a reduction in household incomes, changes in the availability and affordability of nutritious foods, and interruptions to health, nutrition, and social protection services (Headey et al. 2020). We hypothesize that, as a consequence of the COVID-19 crisis, households are forced to adjust their food choices in terms of food quality, towards cheaper and unhealthy food (McDermott and Swinnen 2022), and in terms of quantity, reducing diet diversification and increasing the exposure to malnutrition. The implications of poor nutrition are particularly critical for children under five years of age, as nutritional deficiencies can exert a strong influence on their subsequent growth and development (DNEAP 2010). However, evidence of the effects of COVID-19 on food consumption or nutritional status in richer and poorer countries is still scarce, primarily due to data constraints. After the pandemic, many surveys moved to phone-based or online interviews, which were revealed to be powerful instruments in times when movement and lockdown restrictions are in place. They help to understand some of the socioeconomic consequences of the pandemic, such as job and income losses (Gourlay et al. 2021). However, these findings are all based on crude measures (Abate et al. 2021), given that phone interviews are much shorter (around 15–20 minutes) than in-person ones, and they are based on self-reported and concise answers. As a result, they cannot collect reliable measures of diet quality and nutrition. Some variables indeed require physical measurement, for example, anthropometric measures; other variables require a detailed description of expenditure and consumption, with repeated interviews to avoid long recall periods, as is the case of caloric intake and dietary diversity indices. Abate et al. (2021) found evidence of survey fatigue occurring early on in phone interviews but not during in-person interviews, confirming that while the phone survey mode provides lower costs and is easier to implement in times of crises, it cannot replace in-person surveys for food consumption and anthropometric measurement. Additionally, phone-based surveys only represent that part of the population with phone access. When phone penetration is low, this represents a serious bias in representativeness (Ambel et al. 2021; Ballivian et al. 2015; Brubaker et al. 2021; Demombynes et al. 2013; Gibson et al. 2017; Gourlay et al. 2021; Kastelic et al. 2020).

Other researchers have tried to overcome this issue using different techniques based on simulations and predictions (Laborde et al. 2021a,b; Lakner et al. 2022; Sumner et al. 2020). In particular, Osendarp et al. (2021) used three different models over three different scenarios (pessimistic, moderate, and optimistic) to predict the effect of the COVID-19 crisis on child stunting, wasting and mortality, maternal anaemia, and children born to women with a low body mass index in 118 low- and middle-income countries, finding that an additional US$1.2 billion per year will be needed to mitigate the negative consequences on children's and women's health. An analysis conducted by the Standing Together for Nutrition consortium suggests there could be a 14.3 per cent increase in the prevalence of moderate or severe wasting among children younger than five years due to COVID-19. This would translate to an additional estimated 6.7 million children with wasting in 2020 compared to a counterfactual scenario without COVID-19 (Headey et al. 2020). Although simulations are a powerful tool in anticipating the possible effects of crises and are highly useful for policy-makers to deal with the immediate negative effects, evidence emerging from real data is needed to validate and confirm those predictions.

In this paper we aim to fill this evidence gap using data from a nationally representative in-person household survey covering the months before and after the onset of the pandemic. The data include a detailed consumption module as well as anthropometric measures for children under five years old.

Specifically, the research questions are:

- Did COVID-19 influence household food consumption, and if so to what extent?
- How have children's nutritional outcomes changed due to the COVID-19 crisis?

We use a cross-sectional econometric analysis to look at the variation in different indicators of household food consumption and child nutrition before and after the pandemic. We perform a heterogeneity analysis to understand which factors may be associated with a greater likelihood of being worse off from the crisis. We run a quantile regression to examine the effect along the entire consumption distribution. Finally, we conduct a mediation analysis to investigate the mediating effect the household food environment plays on child nutrition. Some studies have investigated the effects of the COVID-19 crisis on adult nutrition (Lamarche et al. 2021; Pablo et al. 2021; Reza et al. 2021), and on children's nutrition and lifestyle behaviours (Androutsos et al. 2021; Kim et al. 2021; van der Berg et al. 2020; Zemrani et al. 2021). It is, however, important to link the simultaneous effects of the COVID-19 crisis on adults and children within the same household. The household food environment and the parental dietary style are indeed critical factors in child nutrition (Benton 2004). Through the mediation analysis, therefore, we consider the influence that the household food environment plays in affecting the response to the COVID-19 crisis on child nutrition.

We gained five major insights. First, food consumption in quantity (monetary and caloric) declined in response to government restrictions and associated economic effects, but only later in the year. Families probably used savings or sold assets first to keep up their consumption levels before reducing food intake. Instead, food diversity was reduced to a lesser extent. Second, measures of COVID-19 case prevalence are not associated with these outcomes. The economic consequences of the crisis were mainly driven by the government restrictions and their level of enforcement rather than by the health impact of the pandemic. Third, stunting increased in response to government restrictions and associated economic effects. The high pre-pandemic prevalence of stunting suggests that many Mozambican children were already at risk, and the shock then triggered and pushed them over the threshold. Fourth, our heterogeneity analysis shows that the food intake reduction was concentrated in the south of the country and that households who practised subsistence agriculture were able to buffer some of the negative effects. The absolute effect was smaller for the poorer population. This is also confirmed in the results from the quantile regressions. Fifth, child malnourishment was concentrated among newborn children. The results further suggest a redistribution of food among children within a household to the benefit of the firstborn child.

The robustness checks suggest that the real effect is potentially underestimated, although when correcting for multiple hypothesis testing it loses significance except for stunting. The sensitivity analysis confirms that the findings persist even when excluding the provinces of Cabo Delgado and Maputo City, which could be possible outliers.

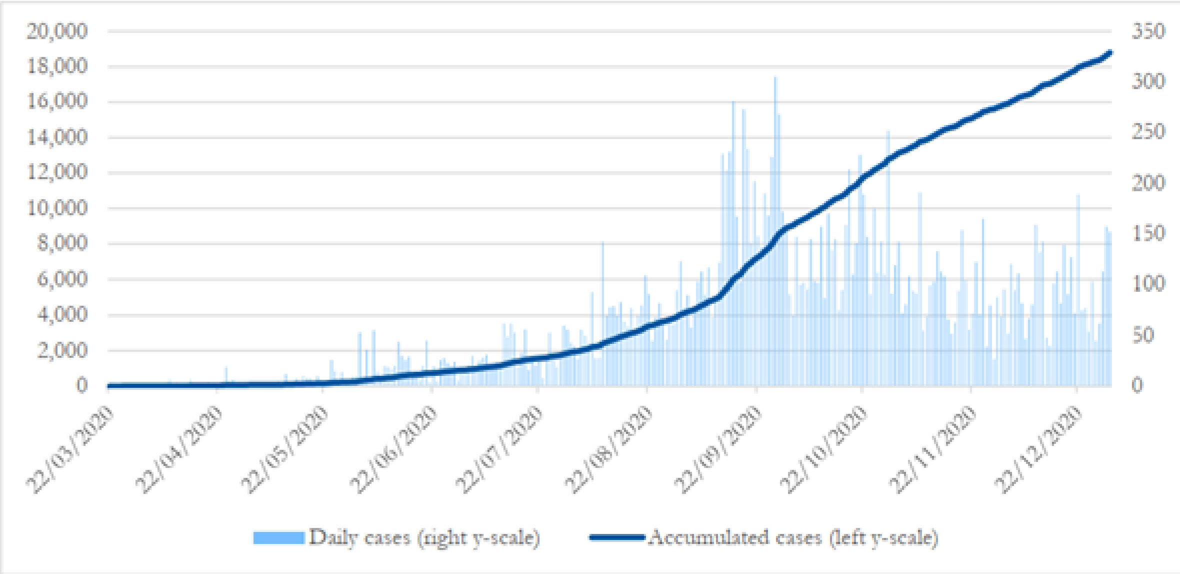
The contribution of this study is threefold. First, it uses primary data collected through face-to-face interviews, including physical measurements of weight and height for children under five years old and detailed questions on food intake. Thanks to this data, we are able to compute correct measures of food consumption and nutrition, comparing the outcomes before and after the COVID-19 outbreak. Second, the results of this analysis can validate some of the early estimates from simulation exercises. Third, it sheds light on the impact of the COVID-19 crisis in Mozambique. Evidence in the country is still scarce, and none of the existing studies looked at the effects of the pandemic and the related restrictions on nutritional outcomes.

The paper is organized as follows. Section 2 provides an overview of the COVID-19 situation in the country during the period under analysis, including the interventions implemented by the government and their association with the infection rate. Section 3 describes the data used and presents some descriptive statistics of relevant variables. We introduce the methodology in Section 4. Section 5 presents and discusses the results of the analysis. Section 6 concludes.

2 Context

This analysis looks at the COVID-19 crisis in Mozambique during the year 2020, which corresponds to the first phase of the pandemic. The first case of COVID-19 in the country was registered on 20 March. However, preventive measures were already in place since the beginning of the month, enabling the population to protect against the spread of the virus at an early stage. The government measures targeted travel restrictions including quarantine, import and export restrictions, early border closure, sanitary measures, an economic recovery plan, and support plans for businesses and exporters. Four different levels of alert were defined in the country, with gathering restrictions that moved from 300 people in level 1 to 10 people in level 3 (Ministério da Saúde 2020). Level 3 was the most stringent one implemented in the country, and was in place at the end of March 2020. At the same time, President Filipe Nyusi announced the state of emergency. The first 120 days focused on preventing the spread of the disease, while the later stage of emergency/calamity seemed to accept both the existence of the virus and the need for envisaging a 'new normal' combined with a slow opening of the economy. The alert level 4, which corresponds to a complete lockdown, was never put in place. In this way, during the so-called first wave of infection from March to June 2020, the country experienced relatively few cases of COVID-19. This continued to be so for a few more months until September 2020, when numbers increased and plateaued at a slightly higher level, as reported in Figure 1.

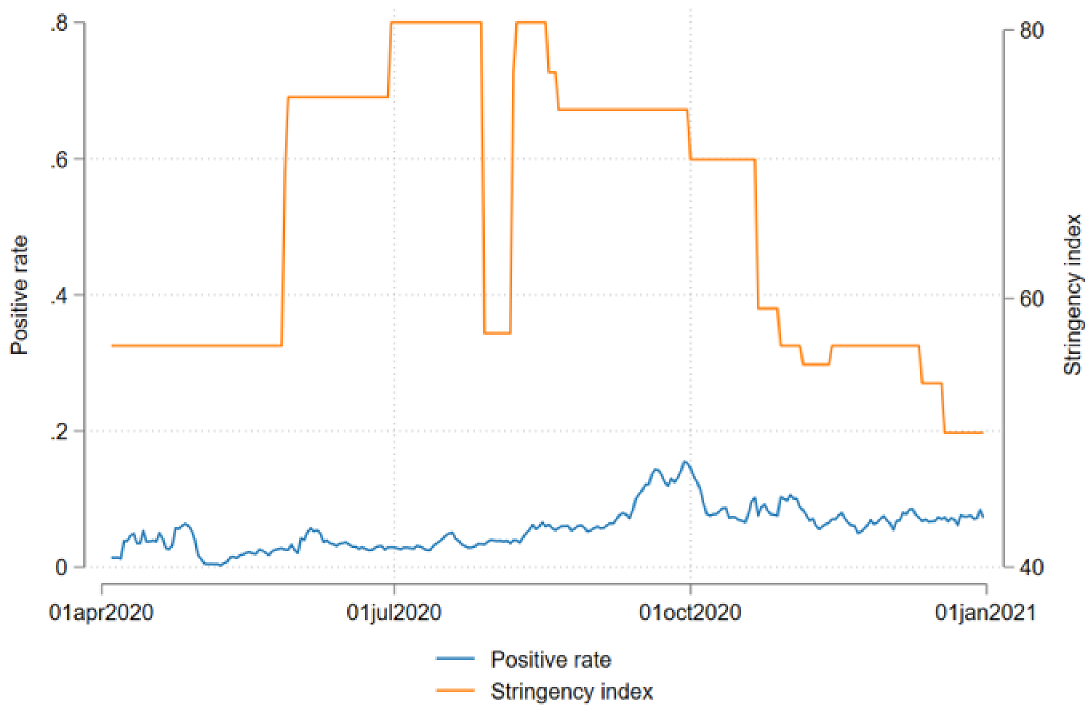
Figure 1: COVID-19 cases registered in Mozambique in 2020, daily and cumulative



Source: authors' elaboration based on data from Mathieu et al. (2020).

The year 2020, therefore, corresponds to the period with the highest stringency level and a low positivity rate, as shown in Figure 2. Our study focuses on 2020, given that the effect on food consumption and nutrition is expected to be mainly driven by the economic downturn caused by the COVID-19 restrictions rather than the direct health effect.

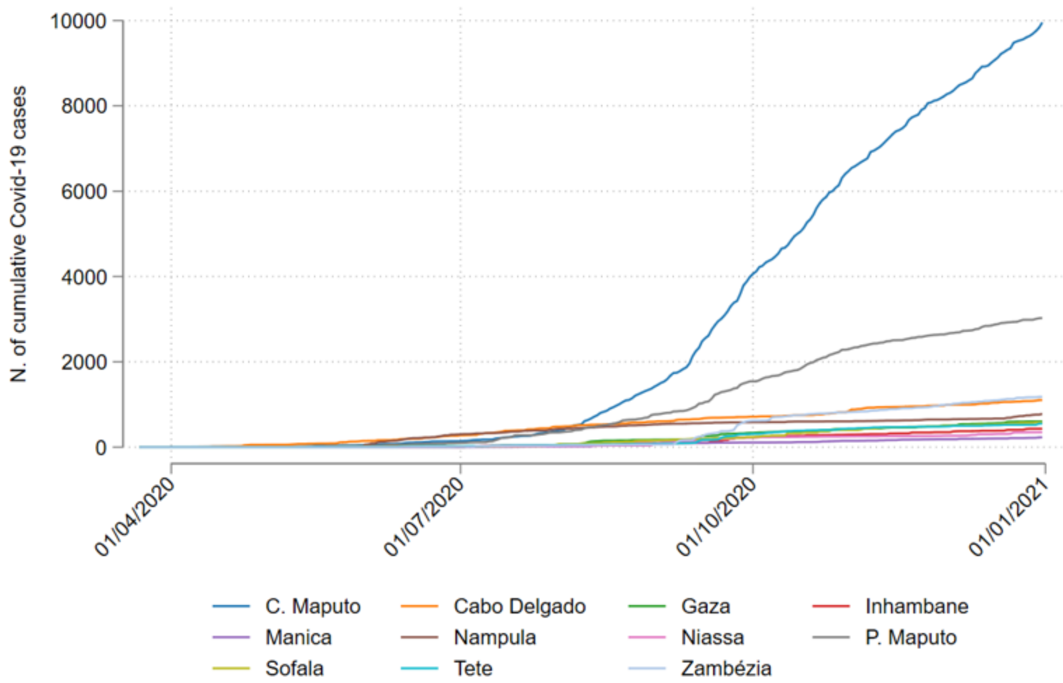
Figure 2: Stringency index and positivity rate in 2020



Source: authors' elaboration based on the Oxford COVID-19 Government Response Tracker (OxCGRT).

Although the COVID-19 cases were quite low during this period, the spread of the virus was different across the country, with some provinces experiencing more cases than others. This is particularly true for the province of Maputo and the city of Maputo, as shown in Figure 3. The different geographic spread can be explained by several factors, including population density, level of enforcement, and rate of testing. Additionally, different economic activities and a higher inflow of foreign travellers could favour a higher infection rate. The geographic and temporal differences are therefore important aspects to consider when analysing the various consequences of the COVID-19 crisis.

Figure 3: Cumulative COVID-19 cases by province.



Source: authors' elaboration compiled from daily bulletins by the Ministry of Health.

The socioeconomic impact of COVID-19 affected the entire country, although some individuals and sectors have been hit more than others, depending on the different transmission channels.

According to the study by Betho et al. (2022), the hardest-hit sectors through the channel of decline in foreign demand are mining, trade, and hospitality. The last two sectors, together with construction and manufacturing, were also affected by lower domestic demand. The impact on labour participation primarily affected urban informal workers and the hospitality sector. Household consumption in Mozambique has been affected by COVID-19 mainly through lower demand for employment, which translated into a reduction in disposable income. Household consumption was estimated to have dropped by 10 per cent (Barletta et al. 2022; Betho et al. 2022; World Bank 2021), but the effect was stronger in urban areas where the density of people restricted movement proportionally more under social distancing rules. Among urban workers, private enterprises and self-employed individuals, especially small traders, show the highest reduction in consumption (Betho et al. 2022).

The Index of Confidence and Economic Climate (*Indice de Confiança e de Clima Económico* (ICCE)) reported that employment was down by 10 per cent and 8 per cent in Q2 and Q3, respectively, compared with Q1 in 2020 (INE 2021a). Simulations on poverty instead found that people working in subsistence agriculture in rural areas are more exposed to an increase in poverty, with about two million people expected to enter poverty in less than a year (Barletta et al. 2022; World Bank 2021).

Reducing consumption and higher poverty can expose households to food insecurity, worsening an already fragile situation. On the supply side, the disruptions in food supply chains and blockages in transport routes, which are particularly obstructive to fresh food, can result in increased levels of food waste and loss, which in turn can reduce food availability and increase food prices. Price variation occurred especially in more integrated markets (Dietrich et al. 2022). Retail prices of white maize, for instance, despite a decrease between March and June 2020 due to the increased post-harvest production, were on average over 15 per cent higher than their year-earlier values (FAO 2020). Other concurrent shocks can deteriorate food security in specific areas of the country. The production shortfalls in the south of the country are likely to have negatively affected households' food supplies and reduced the income-generating opportunities from crop sales in rural areas. In the north, instead, the resurgence in violence in the province of Cabo Delgado in the first half of 2020 has resulted in the internal displacement of about 250,000 people and has severely hampered the delivery of humanitarian assistance, worsening the already high levels of food insecurity (FAO 2020).

In this situation, vulnerable groups are expected to suffer the most. Among them, Mozambican children were already struggling with adequate nutrition levels before COVID-19. The country has registered extremely high levels of chronic malnutrition among children aged 0—4 years (UNICEF 2020c), with 53 per cent of children between 6 and 59 months stunted (WFP 2021). This rate can be further exacerbated through the food insecurity caused by reduced income and disrupted food chains, with a consequent life-long impact on child well-being and cognitive development (Alderman et al. 2006; Ampaabeng and Tan 2013; Mwene-Batu et al. 2021).

Child nutrition is also directly affected by interrupted school-feeding programmes and reduced access to health facilities. Following the closure of schools across the country on 23 March 2020, 235,000 children no longer had access to critical school feeding. UNICEF estimated that 67,500 children would need treatment for malnutrition in the next nine months after the COVID-19 outbreak (UNOCHA 2020).

Additionally, the continuity of essential health services, such as vaccination, treatment of acute malnutrition, and vitamin A supplementation, has declined across the country. According to routine immunization data from the Ministry of Health, all provinces recorded a consistent decline of up to 30 per cent in immunization coverage between March and April 2020 (UNICEF 2020b).

3 Data and descriptive statistics

Data used for this study come from the 2019–20 household budget survey in Mozambique (*Inquérito de Orçamento Familiar*, henceforth IOF) collected by the National Institute of Statistics (INE). Data collection took place from December 2019 to December 2020 through face-to-face interviews, with a three-month break from April to June due to the COVID-19 outbreak. The sample was designed through a probabilistic strategy using a multi-stage stratified sampling plan based on the General Census of Population and Housing 2017. It has been designed to be representative at national, urban and rural, and province levels, as well as for each quarter, meaning that in each quarter all provinces, as well as urban and rural areas, were visited. This allows capturing temporal and geographic variations of expenditure, income, and other socioeconomic characteristics during the year. The survey contains information about general household characteristics, employment, income, daily and monthly expenditures, and household food consumption. It also includes a module with anthropometric data for children under five years old, collected in collaboration with UNICEF. The units of analysis are the household and its respective members. Each selected household was visited for 14 continuous days (approximately a fortnight) in a quarter to reduce recall bias in the food expenditure module.

This dataset is extremely suitable for our analysis for three main reasons. First, interviews took place immediately before and after the COVID-19 outbreak, allowing us to observe the situation before the shock and to look at the effects in the immediate aftermath. Second, given that it has been designed to be a survey with an independent sample for each quarter, this allows us to have representative samples before and after the shock. Third, it represents one of the few existing data that has been collected through face-to-face interviews during the pandemic, including the collection of anthropometric measures. This is particularly relevant for this analysis, given that anthropometric measures, which are our main outcome variables for child nutrition, cannot be collected remotely.

In the cleaning of the data we decided to eliminate those households interviewed in March. These households indeed were interviewed before the first case of COVID-19 was registered in the country, but when the preventive measures were already in place. In this way, we entirely dropped the trimester from March to May, ending up with a sample over three trimesters:[1] the first one, which corresponds to the period before the COVID-19 outbreak, namely from December 2019 to February 2020; the second one from June to August 2020; and the third one from September to December 2020. The final sample comprises 11,836 observations at the household level and 8,524 observations for children under five. Table 1 reports the distribution of households before and after COVID-19, and over trimesters.

Table 1: Distribution of households over trimesters

		N	%
Before COVID-19	Trimester 1	3,326	28.10
After COVID-19	Trimester 2	3,792	32.04
	Trimester 3	4,718	39.86
	Total	11,836	100.00

Source: authors' compilation.

3.1 Outcome variables

The outcome variables used in this analysis can be divided into two groups: on one side we consider the food consumption patterns at the household level. On the other side we focus on the nutritional status of children using anthropometric measures.

Food consumption

IOF 2019–20 includes a specific module on daily food consumption. Questions refer to the quantity of food purchased or consumed from its own production. The data have been collected over a 14-day period,[2] with interviews happening every two days. This reduced the risk of recall errors in food purchased and eaten. From this module, different indicators of household food consumption and dietary quality can be computed. In this analysis we look at different aspects of food consumption: in economic terms, we consider the monetary value of per capita food consumption; in terms of food quantity we look at the per capita caloric intake; in terms of dietary diversity we compute the Household Dietary Diversity Score (HDDS) and the Shannon and Simpson dietary diversity indices.

The HDDS measures the number of different food groups consumed by each household, based on 12 food groups (Anne and Bilinsky 2006).[3] The HDDS serves as a standard indicator of households' economic access to food (Kennedy et al. 2011; Lovon and Mathiassen 2014; Ruel 2003), and it is found to be highly correlated with household-level calorie intakes (Hoddinott and Yohannes 2002) and individual

[1] In this paper we refer to the second and third trimesters as the periods after the COVID-19 outbreak, compared to the first trimester used for the baseline. Therefore the numbering does not correspond to the calendar breakdowns.

[2] We checked the difference between food consumption reported in the first seven and the last seven days, and there is no sign of survey fatigue.

[3] Cereals, root and tubers, vegetables, fruits, meat, eggs, fish, pulses and legumes, milk and dairy products, oils, sugar, and miscellaneous.

micro-nutrient intakes (Fongar et al. 2019; Hatløy et al. 1998; Mekonnen et al. 2020). However, this indicator does not provide information on the relative quantities consumed in each food group.

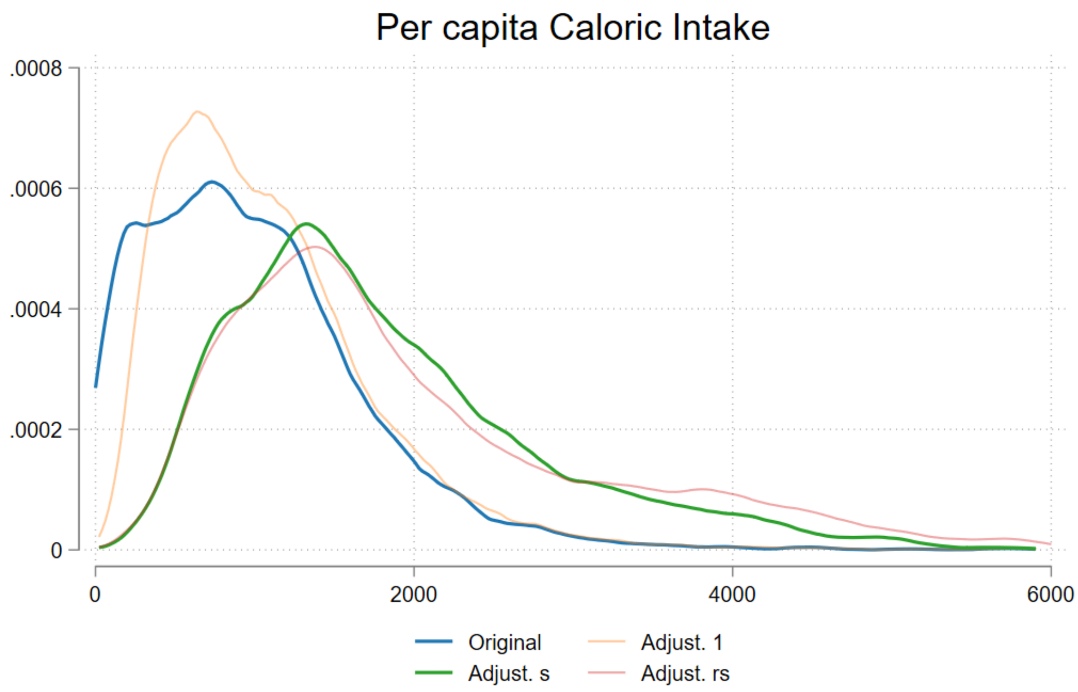
Shannon and Simpson indices instead move from a simple count of food aggregates consumed to measuring the concentration of food consumption in each food aggregate over total food consumption. Both indices were first developed in ecology as entropy measures to reflect the number of different species and how evenly the individuals are distributed among those species (Kiernan 2014), and they can be easily applied to food diversity. The Shannon index takes into account the number of food groups consumed (richness) and their relative abundance (evenness). The Simpson index gives the probability that any two food items randomly selected from an infinitely large food basket will belong to the same food group. The Simpson index is defined as $\sum_{i=1} w_i^2$, where w_i is the share of expenditure on different food subgroups and $i = 1, 2, \ldots, n$ are the categories of food subgroups. The Shannon index instead is defined as $-\sum_{i=1} w_i \ln(w_i)$. The Simpson index ranges from 0 to 1, while the Shannon index ranges between 0 and $\ln(n)$, where a higher value corresponds to higher dietary diversity. Although the two indices are highly correlated, the main difference is that the Shannon index gives lower weight to food subgroups with a higher share of food expenditure, such as cereals and staple food, and comparatively higher weight to food subgroups with a lower share of food expenditure, such as meat (Sharma and Chandrasekhar 2016). Both indices are widely used in the literature to examine the determinants of dietary diversity (see, for example, Karamba et al. (2011), Nguyen and Winters (2011), and Sharma and Chandrasekhar (2016)).

A problem already highlighted in the Fourth National Poverty Assessment of Mozambique and observed in previous IOF surveys is a degree of under-reporting of food consumption, especially in the urban south (DEEF 2016). This is probably due to more diversified diets in these areas, and greater food consumption made away from home, which is more difficult to capture in the food consumption module. These factors increase the probability of non-sampling errors in food consumption reported by the surveyed households. Indeed, in none of the areas in the country the caloric intake reaches the minimum daily energy requirement of 1,800 calories per person per day set by FAO (Bassett and Winter-Nelson 2010).

To correct for this, we applied an adjustment based on the meals description module of the IOF survey, following the methodology applied in the Fourth Poverty Assessment (DEEF 2016). The methodology imputes the adjustment based on the description of the three main meals, namely breakfast, lunch, and dinner. When households reported having eaten a certain food category in the meal description module but did not report that same category in their own consumption or daily expenses, the amount of food of the specific category is then imputed and added in the calculation of total consumption. This amount is determined from the median of the quantity consumed per person per day for each category of food in each spatial domain. To be even more cautious, the imputed amount for each food category is equivalent to half the median amount, here interpreted as a small portion. We considered three adjustments: imputing (i) one quantity per week (1); (ii) one quantity per day (s); and (iii) one quantity per meal (rs). Clearly, the final consumption will be higher when we apply options (ii) and (iii) than in case (i). Figure 4 shows how the distribution of caloric intake changes from the original data to the three different ways of adjustment.

As expected, the distribution shifts to the right, especially with adjustments (s) and (rs). In this analysis we used the adjustment per day (s). In this way, the per capita caloric intake moves from the original 872 calories to the adjusted 1704 calories. The increase is particularly high in urban areas (150 per cent) and the south (175 per cent), as expected. Food consumption includes both purchases and the monetary value of food consumed from own production. Values have been adjusted using a spatial price index to correct for differences in purchasing power across provinces and between rural and urban areas. Both variables of food consumption and caloric intake have been transformed using the inverse hyperbolic sine (IHS) transformation to account for zeros while preserving a similar interpretation as the log transformation (Burbidge et al. 1988; Johnson 1949).

Figure 4: Caloric adjustment based on meal description



Source: authors' elaboration based on the IOF 2019–20.

Child nutrition

We rely on the anthropometric module of IOF 2019–20 to compute measures for child nutrition. These data were collected by the Ministry of Health and the Technical Secretariat for Food and Nutrition Security, under the supervision and coordination of UNICEF Mozambique (INE 2021b).

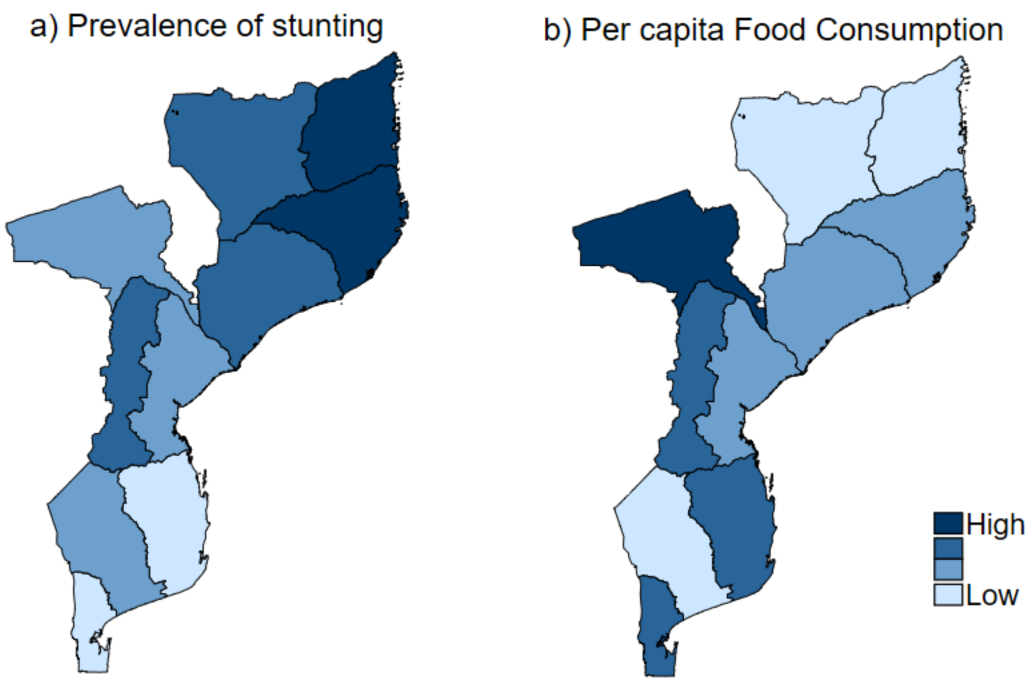
Measures of malnutrition focus on the distance of a given indicator for a child (e.g. height-for-age) relative to the reference population. Specifically, for each child a Z-score can be calculated as $Z_i = (h_i - H_r)/\sigma_r$, where h_i refers to an anthropometric indicator for child i, H_r is the median value for that indicator in the reference population, and σ_r is the standard deviation in the reference population (DNEAP 2010). The reference population comes from the WHO's 2006 data. It is produced from globally representative data to provide a single international standard that best represents the expected distribution of the growth of children under five years of age. Thus, the lower the level of the Z-score, the higher the level of malnourishment. Using this definition, the WHO recommends that children be considered malnourished if they have a Z-score of -2 or less in a given anthropometric index. Weight, height, and age are used to calculate three standard anthropometric indices: weight-for-age, height-for-age, and weight-for-height. Each index indicates different aspects of malnutrition and addresses specific deficits and possible future implications. Height-for-age, for instance, reflects the cumulative effects of undernutrition and infections, and it indicates poor environmental conditions and long-term restriction of a child's growth potential (DNEAP 2010). Weight-for-height indicates acute weight loss, which is a deficit in the amount of tissue and fat compared to the amounts expected for children of the same height. Weight-for-age may be driven by short-term factors, such as recent illness or moderate seasonal fluctuations in the food supply, as well as longer-term deficiencies in access to adequate foods.

Based on the Z-score of these three variables, we computed dummies of malnutrition, equal to 1 when the Z-score is below -2 (or above 2, in the case of overweight), and zero otherwise. Specifically, we considered stunting from height-for-age, wasting and overweight from weight-for-height, and underweight from weight-for-age. Stunting is a physical manifestation of long-term malnutrition, and it represents a risk factor that contributes to infant mortality, and can also be used as a marker of inequalities in human development (Development Initiatives 2020). Wasting is caused by an individual's inability to consume or absorb nutrients, and it might be the result of inadequate food intake or a recent episode of illness (DNEAP 2010). Regarding overweight, this form of malnutrition results from a very low caloric expenditure in relation to the amount consumed, increasing the risk of developing non-communicable diseases later in life.

Among the different indicators of malnutrition, the country suffers most from high levels of stunting. INE estimated that the prevalence of stunting in 2019–20 was 38 per cent at the national level (INE 2021b), which, according to WHO and UNICEF (2019), is classified as 'very high'. The rate is higher for children over 12 months of age, male children, and children living in rural areas. Provinces in the central and northern regions show higher levels of stunting, with the province of Nampula reporting the highest prevalence. Wasting and underweight report lower rates, with a national average of 4.5 and 15.2 per cent, respectively (INE 2021b).

The situation before the COVID-19 outbreak indicates a higher prevalence of stunting in the north of the country, where the levels of food consumption are lower. As expected, the level of stunting and the level of food consumption display an inverse correspondence, as shown in Figure 5.

Figure 5: Pre-pandemic situation of malnutrition and food security across the country



Source: authors' elaboration based on data in IOF 2019–20.

3.2 Summary statistics

Table 2 reports the summary statistics of the main outcome variables and covariates used in the analysis. A full description of the variables considered in the analysis is available in Appendix A1. We can see that, on average, food consumption and caloric intake slightly reduced after the pandemic, while indicators for dietary diversity seem to have remained unchanged. All controls appear quite stable over time, except for tropical livestock units (TLUs), which have declined on average in the aftermath of the COVID-19 crisis, and a slight increase in the percentage of households that practice subsistence agriculture. This could suggest a return to agriculture caused by the crisis, while the sale of livestock may have been used as a coping strategy.

Table 2: Summary statistics

	All sample		Pre-COVID		Post-COVID	
Variables	Mean	Std dev.	Mean	Std dev.	Mean	Std dev.
Outcome variables						
Per capita food consumption	35.9	39.3	37.8	38.1	35.3	39.8
Per capita caloric intake	1576	1168	1599	1285	1568	1124
HDDS	5.94	1.91	5.88	2.07	5.96	1.85
Simpson index	0.51	0.20	0.50	0.22	0.52	0.20
Shannon index	2.08	0.47	2.06	0.50	2.09	0.46
Stunting	0.35	0.48	0.32	0.47	0.36	0.48
Wasting	0.04	0.19	0.04	0.20	0.04	0.19
Underweight	0.13	0.34	0.16	0.36	0.12	0.33
Overweight	0.05	0.22	0.03	0.18	0.06	0.23
Control variables						
Household (HH) size	4.81	2.46	4.80	2.49	4.81	2.45
HH head is female	0.28	0.45	0.27	0.45	0.28	0.45
Asset index	1.12	3.74	1.14	3.90	1.12	3.68
Dep. ratio	1.13	1.00	1.15	1.01	1.13	0.99
HH has children	0.85	0.35	0.85	0.36	0.86	0.35
% employed in HH	0.61	0.30	0.61	0.30	0.61	0.30
HH head has primary educ.	0.50	0.50	0.50	0.50	0.50	0.50
HH owns land	0.78	0.41	0.78	0.41	0.78	0.41
TLU	0.50	8.43	0.71	15.97	0.43	2.47
HH is subsistence ag.	0.62	0.48	0.61	0.49	0.63	0.48
Rural	0.66	0.47	0.66	0.47	0.66	0.47
HH receives social assistance	0.03	0.18	0.04	0.19	0.03	0.18
Access to city (hours)	2.58	2.07	2.72	2.41	2.53	1.94
% of land = savannahs	47.41	29.03	48.77	28.59	46.92	29.16
% of land = grasslands	28.49	27.03	27.93	26.81	28.70	27.11
% of land = broadleaf forest	7.36	10.42	7.22	10.16	7.41	10.51
% of land = urban	3.93	9.59	3.83	9.41	3.97	9.65

Note: household sampling weights applied. Food consumption is reported in meticais per day. HDDS refers to the Household Dietary Diversity Index. TLU refers to tropical livestock units owned by the household. Data on access to city was developed by FAO Hand-in-Hand Initiative (2022). Data on land cover was retrieved from Friedl (2019). A full description of the variables is reported in Appendix A1.

Source: authors' compilation.

4 Methodology

4.1 Main analysis

We quantify the change in household food consumption and child nutrition during the COVID-19 crisis using a pooled OLS/probit, depending on whether the dependent variable is continuous or dichotomous, with province and month fixed effects to account for geographical differences and seasonality. We included a series of control variables, and we clustered standard errors at the district level to correct for possible heteroscedasticity. Household sampling weights are applied to obtain representative estimates. We use the term 'effect' but we acknowledge that we are not identifying a causal mechanism with our estimation strategy. We do not have panel data but only repeated cross-sectional data, so we cannot control for unobserved time-invariant characteristics of the households beyond our control variables. Further, as the shock affected all individuals in the country, we cannot isolate the effect of COVID-19 from other potentially confounding factors. However, any events that lasted throughout the year in a specific region will be captured with the province fixed effects and seasonal shocks by the month fixed effects.

The general specification of the model is:

$$y_{ht} = \alpha_0 + \beta_1 \times COVID_t + \beta_2 \times Controls_{ht} + \varphi_t + \mu_p + \varepsilon_{ht} \tag{1}$$

where the subscripts h and t respectively denote household/child and time; y_h is the outcome variable, namely the variables for food consumption and child nutrition; $COVID_t$ is the variable used to capture the effect of COVID-19. Different definitions of the shock have been applied and are discussed below; $Controls_{ht}$ is a vector of household (and child) characteristics; φ_t is the set of month dummies to account for seasonality; μ_p are province fixed effects; and ε_i is the error term. For the complete list of variables, please refer to Appendix A2.

To identify the effects of COVID-19 and related restrictions, different variables have been considered. First, a simple dummy equal to 1 from July 2020 onwards and 0 otherwise was computed to account for the effect before and after the pandemic outbreak. We call it 'COVID-19'. In this case, we assume that nothing else except COVID-19 occurred during the period under analysis. To look more in-depth at the variation over time, we then considered the dummies for each trimester. In this way, we are able to see if there has been an evolution of the effect over time and if the effect was higher in the immediate aftermath of the pandemic or over the longer term. Additionally, to look at the intensity of the restrictions over time, we computed the average level of the government stringency index, retrieved from the OxCGRT dataset (Hale et al. 2020), by trimester. Finally, we computed two other variables that capture the health shock: the number of confirmed COVID-19 cases over population by province and trimester, and the positivity rate—that is, cases over tests, by province and trimester. These two variables capture not only the variation over time but also across provinces. The positivity rate is a more accurate variable because it reduces measurement error across areas in the country. Indeed, we would expect under-reporting of the number of COVID-19 cases in rural and remote areas rather than in the main cities, where the enforcement and testing capacity was higher. Assuming the same level of under-reporting for the COVID-19 tests, we would expect that the ratio between cases and tests is a reliable measure. As already mentioned, the specific type of shock analysed does not permit us to fully identify a causal effect. The effect of the COVID-19 crisis has been transmitted simultaneously through different channels, including health, employment, and food markets, and at various levels (rural vs urban, provincial, and national). Even though we know anecdotally about different levels of enforcement or severity (as described in Section 2), we cannot isolate one specific channel. Restrictions have been implemented at the national level, and even if a clear distinction at the regional level were possible, as used in Amare et al. (2021) for the case of Nigeria, the identification strategy could not include spillover effects among regions and the aggregate shocks that have occurred through the international market. The variable of COVID-19 cases alone does not necessarily correlate with the intensity of socioeconomic restrictions at the local level. Indeed, when using daily data retrieved from OxCGRT, we found that, in Mozambique, the number of COVID-19 cases does not correlate with the stringency index.

Nevertheless, we think this analysis is still worthwhile and, although descriptive, can provide valuable insights into the nutritional situation in the country in the aftermath of the pandemic. Indeed, given the short period considered and the absence of other significant shocks during that time, we can assume that any changes that have occurred can be attributed to COVID-19. Additionally, if we find that a coefficient goes in the opposite direction than the trend observed in the last years in the country, this should reassure us that we are capturing the effect of the specific shock, and not merely a time trend.

4.2 Heterogeneity analysis

To better understand possible channels and to identify which households and individuals have been affected more than others, we conducted a heterogeneity analysis. This is done by interacting the variable used as a proxy for the aggregate COVID-19 shock with the variable of interest for the heterogeneity. The model is specified as:

$$y_{ht} = \alpha_0 + \beta_1 \times Covid_t + \beta_2 \times (Covid_t \times C_{ht}) + \beta_3 \times C_{ht} + \beta_4 \times Controls_{ht} + \varphi_t + \mu_p + \varepsilon_{ht} \qquad (2)$$

We are interested in the coefficient β_2 of the interaction term, where C_{it} is the household/child characteristic of interest. We consider different variables that we think are relevant in defining the level of food consumption and nutrition and the related response to COVID-19 on the specified outcome. At the household level we look at the gender of the household head, the location of the household (if rural/urban, and south/centre/north), the level of education of the household head, if the household practices subsistence farming,[4] if the household has children, if the household lives in a district with high levels of malnutrition,[5] and the wealth level (poor vs rich households).[6]

Evidence shows that female-headed households manage household resources and cope with shocks in a different way than male-headed households (Asfaw and Maggio 2018; Mason et al. 2015; Rogers 1996). The geographical location is also relevant in determining a different response to the shock. Indeed, the type of economy, as well as the income composition of the households, can differ between rural and urban locations, and between the north and the south of the country. The south is more urbanized and more connected to the markets of neighbouring countries, such as South Africa. Therefore, it is expected to be more vulnerable to restrictions on international trade, as simulated by Betho et al. (2022). The north and centre instead are more rural, with households mainly relying on subsistence agriculture, and therefore they are less integrated with local and global markets. The education of the household head and the level of household wealth are also possible predictors of different coping strategies to deal with the crisis, as documented in several studies (e.g., Farzana et al. 2017; Ibukun and Adebayo 2021; McKenzie 2003; Tefera and Tefera 2014). Living in a district with a high level of child malnutrition could denote a general level of deprivation at the community level, both in terms of services and economic opportunities.

At the child level, we consider whether the child is the firstborn, the age cohorts, specifically newborn children, the gender of the child, and the average prevalence of stunting in the district where the child lives. Newborn children are expected to be affected more by the crisis because they are born immediately before or during the crisis. They are also more exposed to experiencing adverse functional consequences if stunted, particularly in the first 1,000 days from conception (WHO 2014). Extensive literature demonstrates the preference of parents towards the firstborn, especially if male, in many low-income countries, which leads to an unequal distribution of resources among children within the same household (Bishwakarma and Villa 2019; Jayachandran and Pande 2017; Sahn and Stifel 2002). Finally, in normal conditions, we would expect that the likelihood of being malnourished is higher if the child lives in a district where the overall levels of malnutrition are high. This relation can be caused by a lack of water and sanitation services in the area, poor infrastructure, especially health facilities, and few economic opportunities. However, given the peculiar nature of the aggregate shock under analysis, the

[4] A household is defined to practice subsistence agriculture when the share of food consumption from own production over total food consumption is >50 per cent.

[5] Malnutrition here is proxied by the average prevalence of stunting at the district level computed at baseline to capture the pre-pandemic situation.

[6] Wealth is defined in terms of assets. The asset index is computed with principal component analysis using indicators of housing quality and access to public service infrastructures, such as sanitation and electricity. A household is defined as poor if it belongs to the first and second lowest wealth quintiles.

association is not clear. If indeed wealthier households have been hit more, we should expect an opposite result, given that these households are historically located in districts with low rates of stunting (UNICEF 2020a).

4.3 Quantile analysis

With the regressions described in the previous sections, we can only estimate the mean value. To shed light on the effect along the distribution, we can model the entire distribution of the data using conditional quantile regression. In quantile regression, $Q_q(y|x)$ is the conditional quantile point for the distribution y, given a set of covariates x. The coefficients estimated in this way quantify the expected change in the distribution of y for the quantile point q as the variable of interest increases by one unit net of the other covariates. The corresponding equation is:

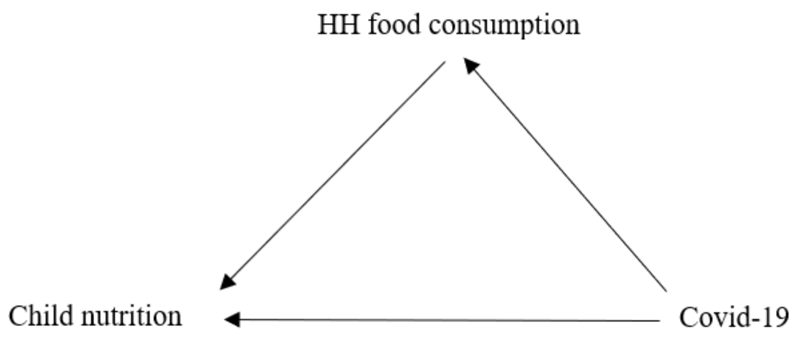
$$Q_q(y|x) = x'\beta_q \tag{3}$$

where we consider the same covariates as in Equation (1), but only continuous outcome variables. In this way, we can understand if, for instance, households with a better diet diversity or children with higher levels of stunting were affected differently than households and children in the lowest percentiles of the distribution.

4.4 Mediation analysis

To explore the role of the household food environment in affecting children's diets, we computed a mediation analysis. The household food environment and the parental dietary style are critical factors in child nutrition (Benton 2004). Parents influence their child's nutrition in two ways: directly, as they are the members of the household that take food consumption decisions for the entire family, and indirectly through modelling, a cognitive process through which individuals observe others' behaviours and create their own beliefs based on these observations (Bandura 1977). Studies have shown parent–child correspondence in the intake of foods and drinks, particularly for mothers (e.g., Cooke et al. 2004; Fisher and Birch 2002; Fisk et al. 2011; Fry et al. 2011; Grimm et al. 2004; Sonneville et al. 2012; Wroten et al. 2012). At the same time, the impact of shocks on households can have unequal effects on individual household members (Alderman et al. 1995; Hoddinott 2006). The graphical model representing the relationship between household food decisions and child nutrition in the impact of COVID-19 is shown in Figure 6.

Figure 6: Diagram path of mediation analysis



Source: authors' compilation.

In Figure 6 we can see that the impact of COVID-19 on child nutrition can be both direct and mediated by the effect of the household food environment. In this way, it is possible to separate the two avenues, isolating the role that household food consumption plays in mediating the effect on child nutrition. The corresponding system of equations is:

$$\begin{cases} FoodConsHH_{ht} = \alpha_0 + \beta_1 \times Covid_t + \beta_2 \times ControlsHH_{ht} + \varphi_t + \varepsilon_{1_{ht}} \\ ChildNutrition_{iht} = \alpha_1 + \beta_3 \times Covid_t + \beta_4 \times FoodConsHH_{ht} + \\ \qquad\qquad + \beta_5 \times ControlsChild_{it} + \varphi_t + \varepsilon_{2_{iht}} \end{cases} \tag{4}$$

We considered the same control variables used in Equation (1), specific for households and children respectively. The second equation in the system includes the direct effect of COVID-19, the direct effect of household food consumption, and the indirect effect of COVID-19 mediated by the household food environment on child nutrition. For the sake of simplicity, we only considered the COVID-19 dummy as a proxy for COVID-19. We had to exclude province fixed effects because of convergence problems.

5 Results

5.1 Main analysis

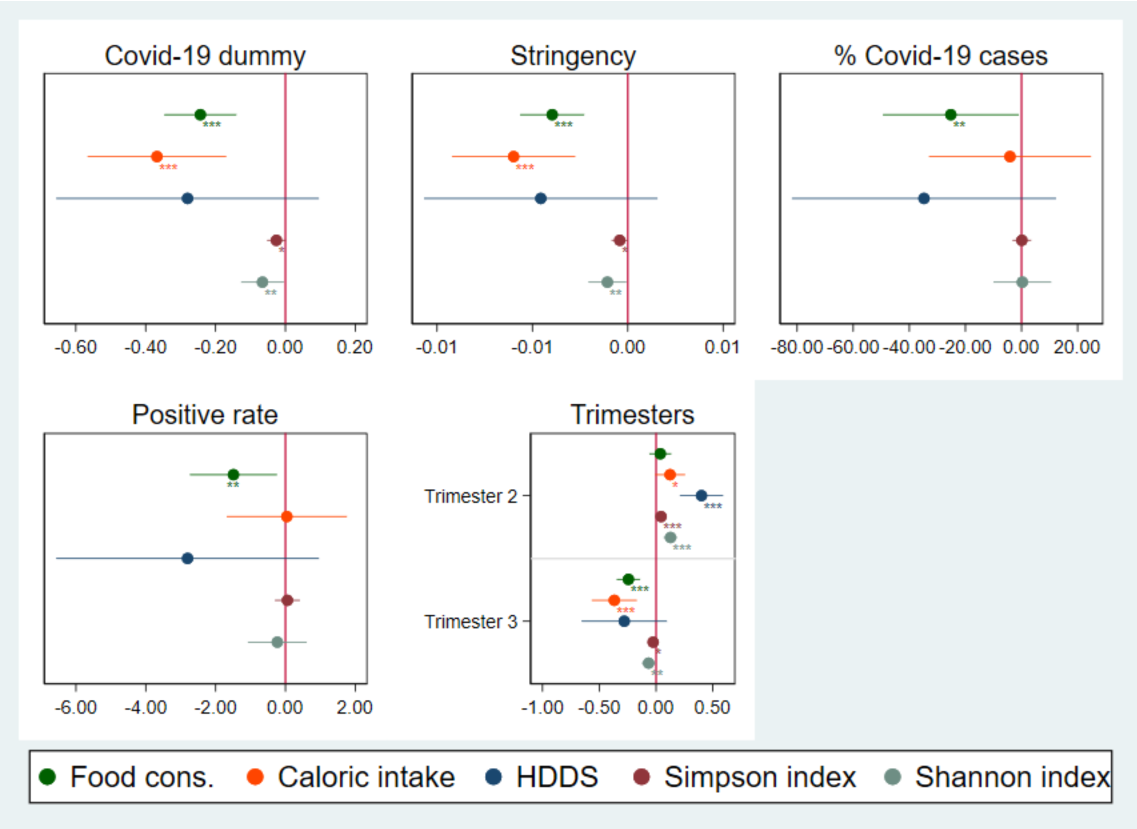
Table 3 reports the results of the pooled OLS with per capita caloric intake as the dependent variable (used as an example), over different specifications. For the sake of simplicity, we use the COVID-19 dummy as the proxy for the aggregate COVID-19 shock. In Figure 7, instead, we show the estimated coefficients using the alternative proxies of the shock. Model (1) is the simplest one, where no controls and no fixed effects are included. Model (4) is the most complex one and corresponds to the one reported in Equation (1). As shown in the table, it is important to include monthly fixed effects. Indeed, with their inclusion the coefficient of the COVID-19 dummy becomes negative and significant, suggesting that seasonality highly affects the level of food consumption over the year. Also, the R-squared increases, suggesting that model (4) is the most suitable to explain variation in food consumption. We can also verify that most covariates correlate with the quantity of food consumption as expected. For example, larger households with relatively more dependents in rural areas have, on average, lower levels of caloric intake. In contrast, asset-rich households and those with a higher share of members employed have higher levels.

When looking at the coefficient of different definitions of the COVID-19 shock on different household food consumption variables, reported in Figure 7, we see some interesting patterns. The COVID-19 dummy is always negatively associated with the variables of food security, suggesting that after the COVID-19 outbreak there has been a reduction both in the quantity of food consumption and in the quality.

The stringency index reports similar results, suggesting that the change in household food consumption is linked to the restrictions imposed by the government and specifically to their level of stringency. Therefore, as expected, more stringent measures correspond to a reduction in food consumption, caloric intake, and dietary diversity. Instead, the two variables related to the COVID-19 cases seem to have a similar effect on food consumption but a null effect on dietary diversity. This would suggest that variables more related to the health side of the pandemic are not perfect predictors of the economic consequences of the crisis. A higher number of COVID-19 cases could also be the result of lower enforcement of the restrictions.

Interesting dynamics emerge when looking at the effects over time (trimesters). Indeed, we notice that the effect is not immediate, but it mainly occurs in the third trimester. This could suggest that in the aftermath of the pandemic people were using different coping strategies to offset the reduction in income, such as relying on savings or selling assets. However, these strategies turned out to not be sufficient or sustainable over time.

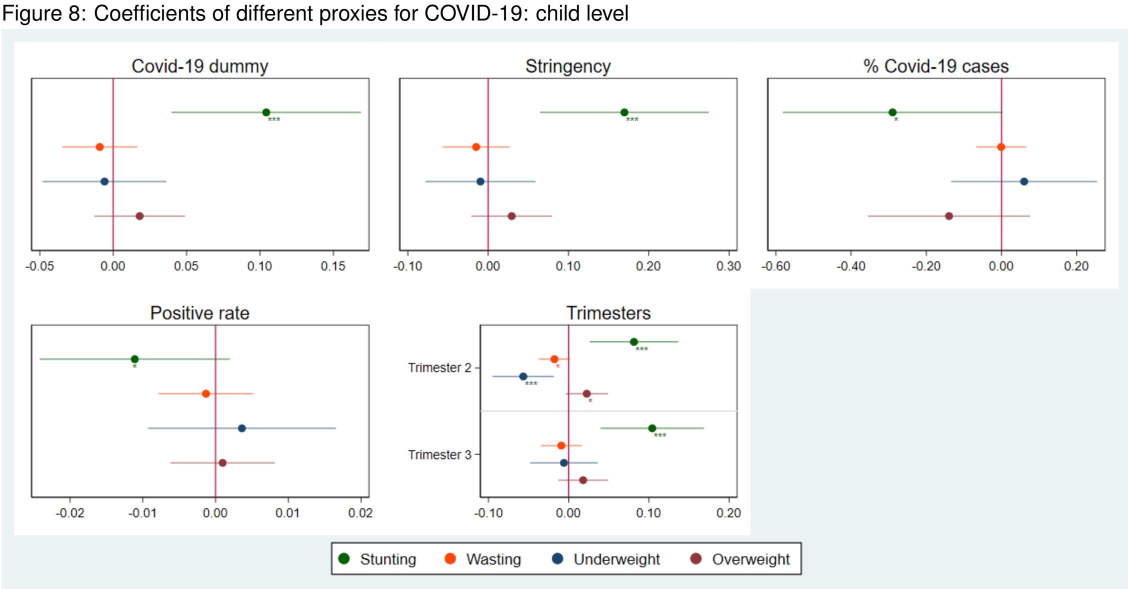
Figure 7: Coefficients of different proxies for COVID-19: household level



Note: dots are coefficients estimated from a linear regression. The COVID-19 dummy is a time dummy equal to 1 from July 2020 onwards and 0 otherwise. Household sampling weights applied. Standard errors clustered at the district level. Bars are 95 per cent confidence intervals. The full results table is reported in Appendix A2.

Source: authors' elaboration based on data from IOF 2019–20.

Figure 8: Coefficients of different proxies for COVID-19: child level



Note: dots are average marginal effects estimated from a probability regression. The COVID-19 dummy is a time dummy equal to 1 from July 2020 onwards and 0 otherwise. Household sampling weights applied. Standard errors clustered at the district level. Bars are 95 per cent confidence intervals. The full results table is reported in Appendix A2.

Source: authors' elaboration based on data from IOF 2019–20.

Table 3: Pooled OLS, different specifications

Variables	(1)	(2)	(3)	(4)
COVID-19 dummy	0.0390	0.0350	0.0428	–0.368***
	(0.0522)	(0.0530)	(0.0502)	(0.101)
HH size		–0.0554***	–0.0542***	–0.0533***
		(0.00717)	(0.00583)	(0.00590)
HH head is female		–0.0651**	–0.00803	–0.00730
		(0.0296)	(0.0281)	(0.0282)
Asset index		–0.0156	0.0220**	0.0224**
		(0.0100)	(0.00883)	(0.00863)
Dep. ratio		–0.0525***	–0.0604***	–0.0587***
		(0.0170)	(0.0157)	(0.0150)
HH has children		–0.0703	–0.116**	–0.119***
		(0.0452)	(0.0455)	(0.0449)
% employed		0.109*	0.129**	0.138***
		(0.0625)	(0.0549)	(0.0526)
Head has some primary educ.		–0.0282	–0.0513*	–0.0521*
		(0.0316)	(0.0267)	(0.0265)
HH owns land		0.0728	0.0605	0.0682
		(0.0562)	(0.0423)	(0.0419)
TLU		0.000442	0.000791**	0.000813**
		(0.000629)	(0.000397)	(0.000390)
HH is subsistence ag.		0.109	0.0745	0.0798
		(0.0972)	(0.100)	(0.0998)
Rural		–0.276***	–0.135*	–0.141*
		(0.0863)	(0.0708)	(0.0727)
HH receives social assistance		–0.119*	–0.0950	–0.0975
		(0.0672)	(0.0666)	(0.0648)
Access to city (in hours)		–0.00553	–0.00265	–0.00116
		(0.0168)	(0.0145)	(0.0146)
% of land = savannahs		–0.00237	–0.00361*	–0.00348
		(0.00225)	(0.00218)	(0.00224)
% of land = grasslands		–0.00185	0.000200	0.000344
		(0.00271)	(0.00222)	(0.00225)
% of land = broadleaf forest		0.000910	–0.00462	–0.00423
		(0.00547)	(0.00501)	(0.00495)
% of land = urban		–0.0139**	–0.00590*	–0.00593*
		(0.00573)	(0.00332)	(0.00335)
Constant	7.693***	8.337***	7.721***	7.701***
	(0.0526)	(0.217)	(0.185)	(0.192)
Province FE	No	No	Yes	Yes
Month FE	No	No	No	Yes
Observations	11,836	11,836	11,836	11,836
R-squared	0.000	0.064	0.139	0.144

Note: dependent variable: IHS transformation of per capita caloric intake. The COVID-19 dummy is a time dummy equal to 1 from July 2020 onwards and 0 otherwise. Household sampling weights applied. Regression estimated through a linear model. Clustered standard errors at the district level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: authors' elaboration based on data from IOF 2019–20.

In terms of child nutrition, we find that only stunting seems to have significantly increased in the aftermath of the pandemic, as reported in Figure 8. Stunting usually captures long-term developmental challenges. However, given that the prevalence of stunting was already very high before the crisis, we expect many children to have been at risk of being stunted. The results suggest that stunting, therefore, is more sensitive to negative shocks than the other anthropometric measures. Indeed, it is positively and significantly correlated with the COVID-19 dummy, the level of stringency, and the trimester dummies. As in Figure 7, we see an opposite effect when considering the COVID-19 cases and the positivity rate.

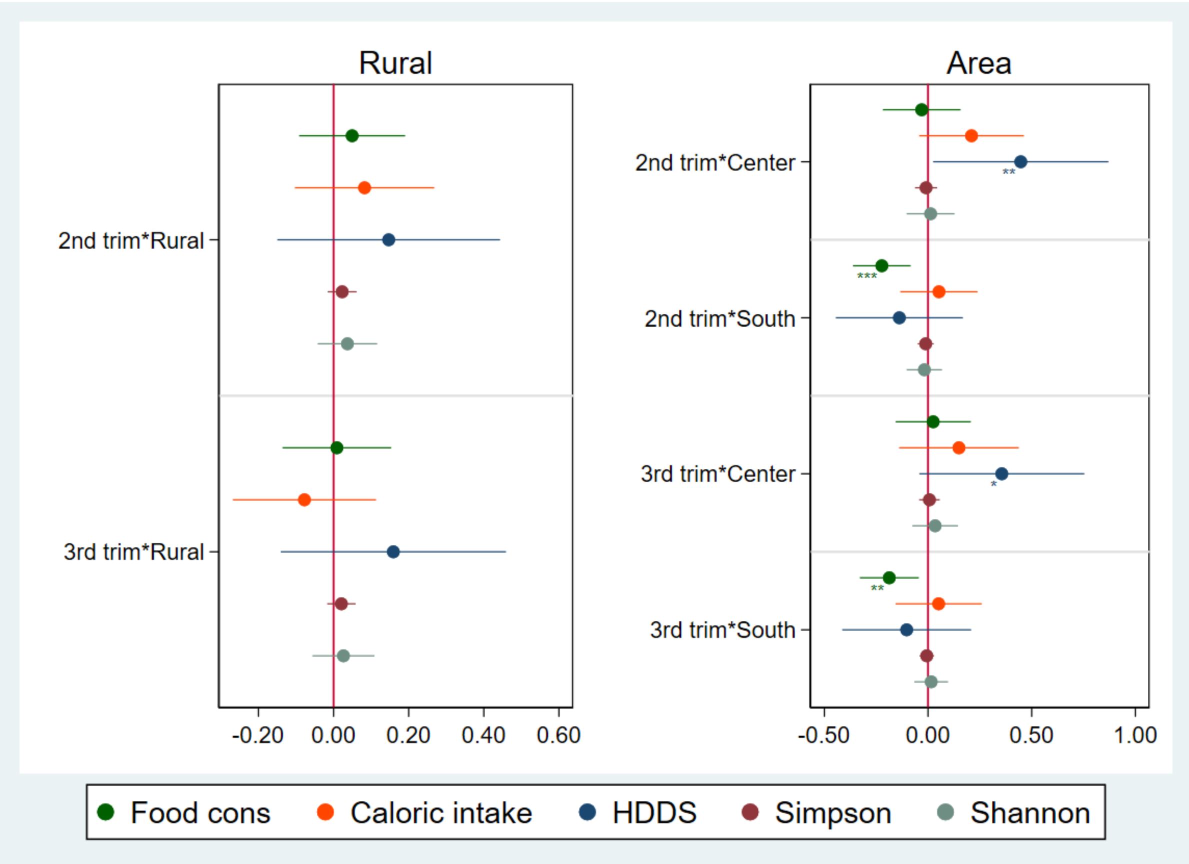
We do not see the same path over time across the different outcomes of nutrition. Wasting and underweight show a trend similar to the one observed for the variables of household food consumption. They report a reduction in the second trimester, which turned out to be insignificant and closer to zero in the third trimester. This result is plausible, given that wasting and underweight are more responsive to short-term shocks, and they follow the same effect on household food consumption. Instead, stunting reports an increase immediately, and the effect seems to intensify in the third trimester. This can be explained by other factors unrelated to the household food environment that negatively affected the level of stunting in the country. Disruption of the health systems and water supply operations during the emergency period, for instance, could affect maternal and child health (UNICEF 2020c).

5.2 Heterogeneity analysis

When we consider the differentiated effect over different household characteristics, some interesting patterns emerge. At the geographical level (Figure 9), we find that being located in the south is negatively correlated with food quantity and diet diversity in the aftermath of the pandemic, especially in terms of food consumption. Compared to the northern region (used as the reference), the southern region indeed presents a negative effect in terms of food consumption.

These results confirm what was simulated by Betho et al. (2022), namely that households in urban areas and in the south of the country were hit more by the COVID-19 crisis than households in the rest of the country. Movement restrictions and trade shocks were more prevalent in the urban centres of the south of Mozambique.

Figure 9: Heterogeneity analysis: geographical variables

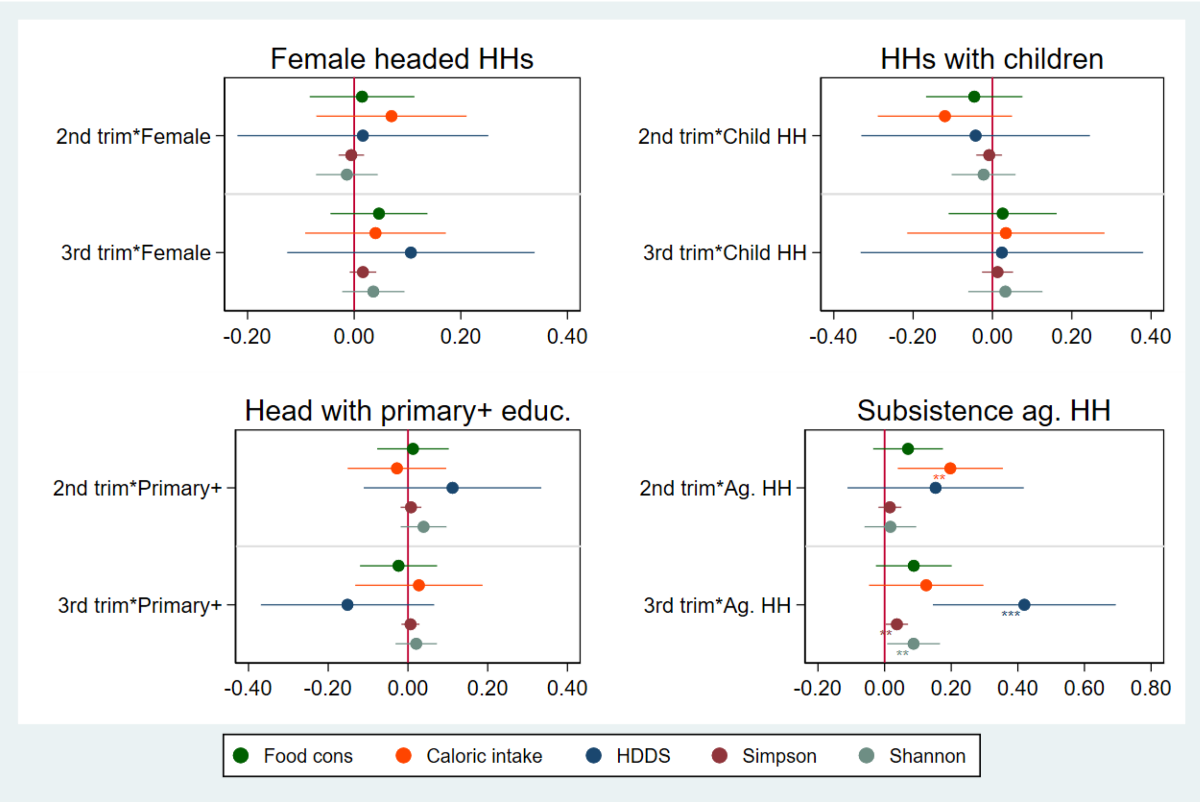


Note: dots are coefficients estimated from a linear regression. Household sampling weights applied. Standard errors clustered at the district level. Bars are 95 per cent confidence intervals. The full results table is reported in Appendix A2.

Source: authors' elaboration based on data from IOF 2019–20.

In terms of household characteristics, we do not see a different pattern between female- and male-headed households, or between households with and without children (Figure 10). A similar result can be found when considering the level of education of the household head. Instead, households that practice subsistence agriculture are better off compared to the other households in the aftermath of the COVID-19 outbreak. This is particularly true in terms of dietary diversity. Indeed, the coefficients of HDDS, Simpson index, and Shannon index are positive and significant in the third trimester. Subsistence agriculture might enable these households to maintain a certain quantity and quality of food independent of market interruptions. This is in line with the findings of Dietrich et al. (2022), who found that segmented markets less dependent on other markets for imported commodities were less affected by the reductions in mobility than integrated markets.

Figure 10: Heterogeneity analysis: household characteristics

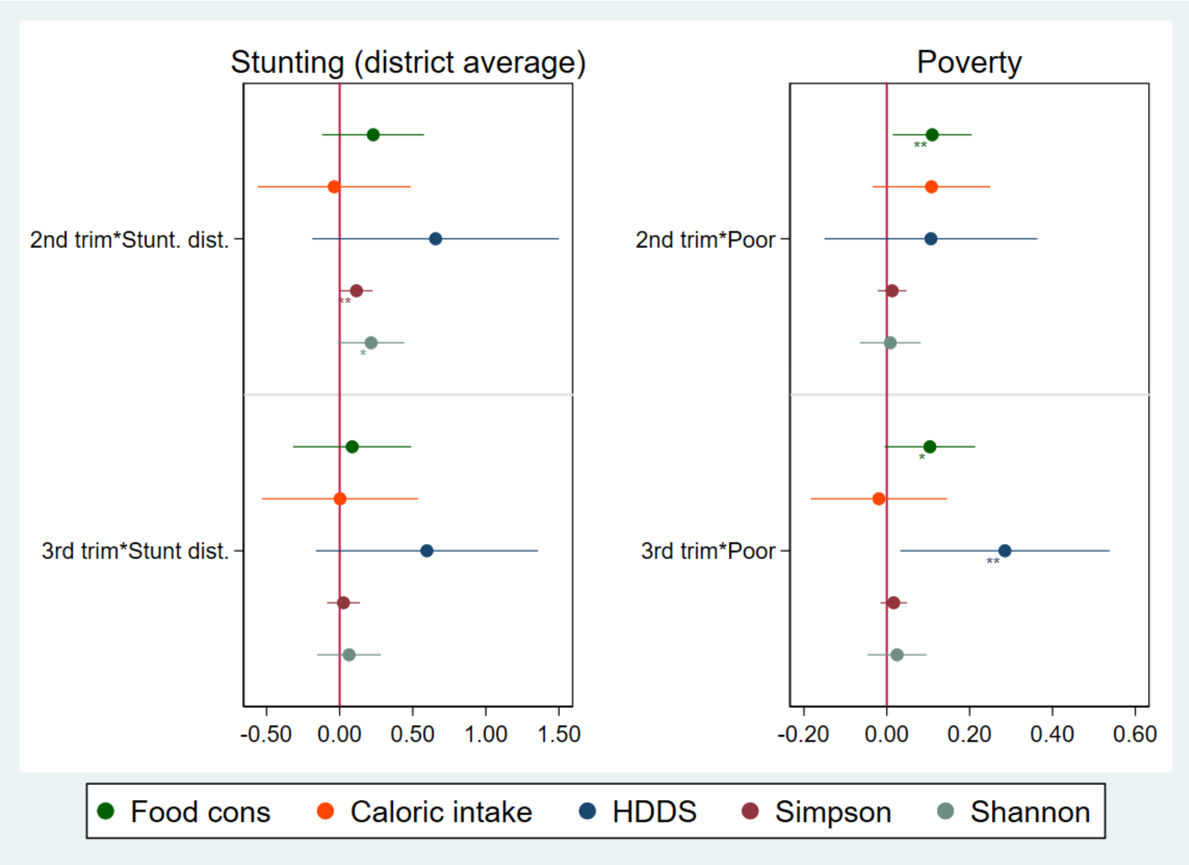


Note: dots are coefficients estimated from a linear regression. Household sampling weights applied. Standard errors clustered at the district level. Bars are 95 per cent confidence intervals. The full results table is reported in Appendix A2.

Source: authors' elaboration based on data from IOF 2019–20.

Living in a district with a high level of malnutrition (proxied by the prevalence of stunting) seems to have a slight positive effect on dietary diversity in the second trimester, but then the effect disappears in the third trimester. Overall, it seems to not be a determinant factor in having a change in food consumption due to the COVID-19 crisis (Figure 11). Instead, the poorest households seem to have been less affected than the richer ones. Although this could appear controversial, this result is aligned with the findings in other studies (Chitiga-Mabugu et al. 2021; Mahmud and Riley 2021). Indeed, the magnitude of the effect of the aggregated COVID-19 shocks in absolute monetary terms is expected to be higher for wealthier people, but the relative effect is higher for the poor (Barletta et al. 2022).

Figure 11: Heterogeneity analysis: malnutrition and poverty

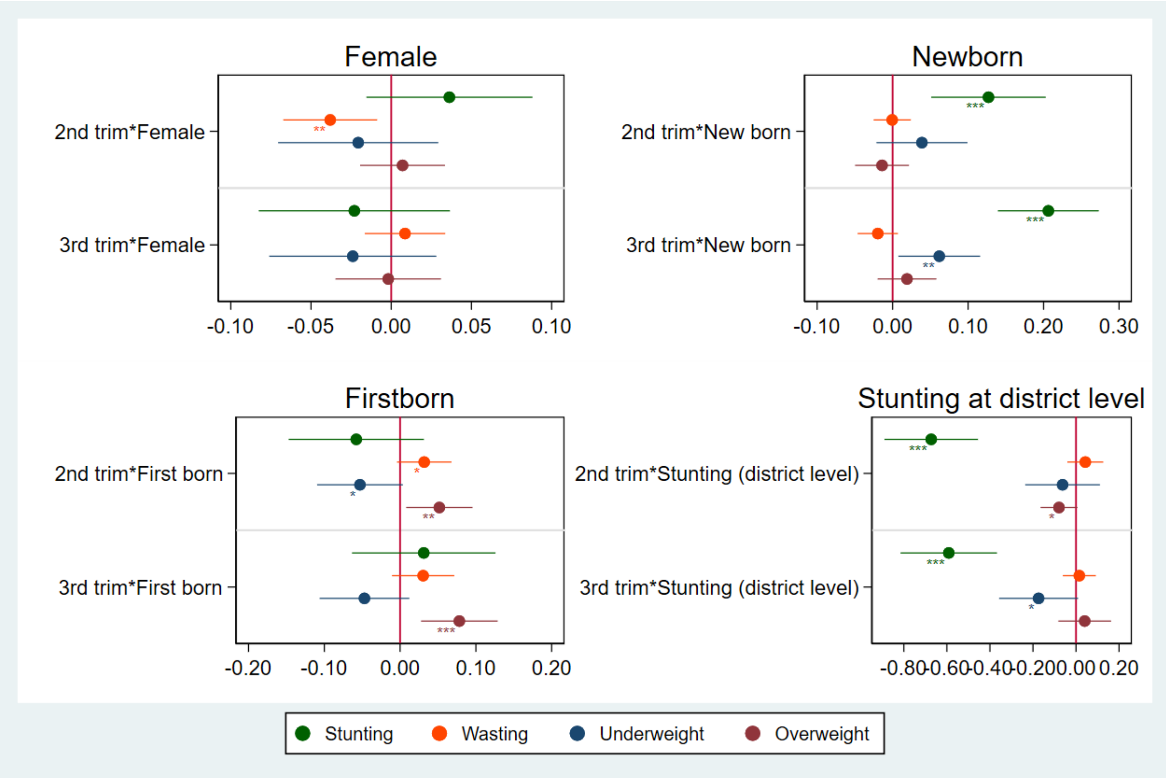


Note: dots are coefficients estimated from a linear regression. Household sampling weights applied. Standard errors clustered at the district level. Bars are 95 per cent confidence intervals. The full results table is reported in Appendix A2.

Source: authors' elaboration based on data from IOF 2019–20.

In terms of the heterogeneous effect of COVID-19 on nutrition over different child characteristics, the first finding that emerges from Figure 12 is that there is no gender effect. This means that girls and boys experienced a similar effect on nutrition in the aftermath of the pandemic. Instead, newborn children have been more negatively affected than older children. This is particularly true for stunting and in part for underweight. This confirms the expectation that younger children, especially the ones born immediately before the pandemic, could suffer more than others. In the early stages of life, in particular during the first 1,000 days, nutrition has a crucial role in shaping the immunological, cognitive, and physical development of the individual (Larson-Nath and Goday 2019; Mayneris-Perxachs and Swann 2019), with long-term health consequences, increasing the risk for developing diseases later in life (Walker et al. 2007), and leading to poor school and work achievement (Alderman et al. 2006). Firstborn children instead report a positive and significant coefficient of overweight. This result could suggest that there has been a redistribution of food among children, with parents prioritizing the firstborn over the other children. Living in a district with a high level of stunting seems to be associated with a lower probability of child malnutrition in the aftermath of the pandemic. Districts with a high prevalence of stunting are mainly located in the north of the country, where the poorest part of the population lives. Therefore, also at the child level, the findings confirm that the shock mainly affected the richest households in the south of the country, where aggregate levels of stunting are lower.

Figure 12: Heterogeneity analysis over child characteristics



Note: dots are average marginal effects estimated from a probability regression. Household sampling weights applied. Standard errors clustered at the district level. Bars are 95 per cent confidence intervals. The full results table is reported in Appendix A2.

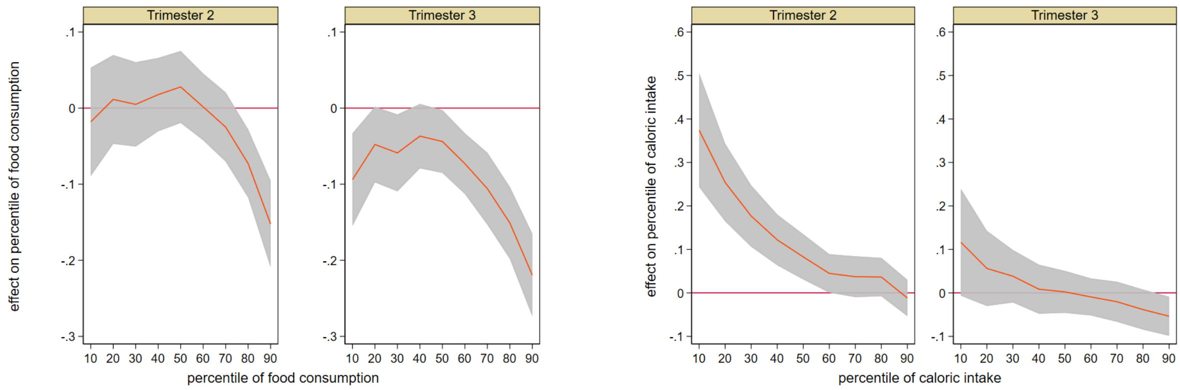
Source: authors' elaboration based on data from IOF 2019–20.

5.3 Quantile regression

In this section, we look at the change in the distribution, divided into percentiles, over the continuous outcome variables at the household level.[7] The first thing we can notice is that the households in the highest percentiles experience the negative effect more, especially regarding food consumption and caloric intake (Figure 13). These findings are in line with the results of the heterogeneity analysis by poverty status. Wealthier families, which have higher levels of food expenditure and dietary diversity, have been hit hardest in absolute terms (Figure 14). However, in the quantile regression we observe that also households at the lowest level of food consumption suffered relatively more in the third trimester. In contrast, the effects on caloric intake always display a positive sign for the lowest percentiles, with larger effects in the second trimester. The first trimester in Mozambique is the rainy period and is also called the 'hungry period' due to widespread food scarcity in rural areas, so it is a common pattern to observe higher food consumption in consequent trimesters (Salvucci and Tarp 2021). Similar patterns are observed for dietary diversity. Taken together, these results suggest that families with relatively low caloric intake and dietary diversity improved their diet in the second trimester after the pandemic onset, but could not uphold this change as the pandemic progressed.

[7] HDDS is not included in the quantile regression since it is not a continuous, but rather a discrete variable.

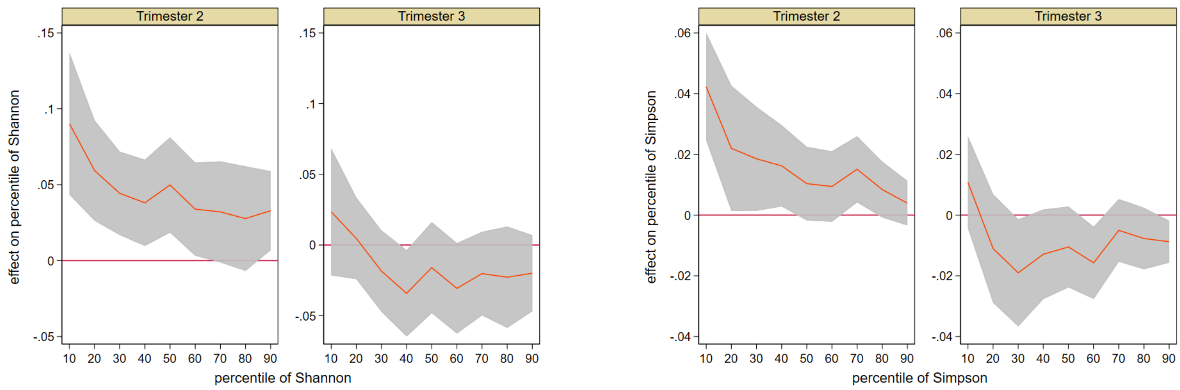
Figure 13: Percentile regression: food consumption and caloric intake



Note: simultaneous quantile regression with 100 bootstrap replications. Regressors include the same control variables and province and month fixed effects of the general model.

Source: authors' elaboration based on data from IOF 2019–20.

Figure 14: Percentile regression: dietary diversity



Note: simultaneous quantile regression with 100 bootstrap replications. Regressors include the same control variables and province and month fixed effects of the general model.

Source: authors' elaboration based on data from IOF 2019–20.

5.4 Mediation analysis

We conducted a mediation analysis to disentangle the direct from the indirect effects of the COVID-19 crisis on child malnutrition. Our interest lies in the role of the household food environment in channelling some of the crisis effects. For example, if a household consumes less food due to government restrictions, how does this influence the malnutrition outcomes of the children in this household? Table 4 reports for each outcome of child nutrition (columns) the direct effects of the household food environment (food consumption, caloric intake, HDDS, Shannon and Simpson indices), the direct effect of COVID-19 (COVID-19 dummy), and the indirect effect of COVID-19 mediated by the household food environment variable.

We observe that the direct effect of COVID-19 on child nutrition is always positive, as found in the previous analysis. Specifically, we see a significant increase in stunting and underweight. The direct effect of household food security and dietary diversity on child nutrition is only significant for food consumption. There is also a weak negative relationship between the Shannon index of dietary diversity and stunting. The lack of a significant relationship could be due to two factors. The first explanation is an unequal distribution of food within the family so that the per capita value does not state what the children actually consume. The other explanation relies on the limitations of some of the indicators. Caloric intake is not an indicator of the quality of diet in terms of micronutrients. At the same time, the HDDS does not consider the quantity consumed in each food group.

Table 4: Direct and indirect standardized effects, mediation analysis

	Stunting	Wasting	Overweight	Underweight
Panel (a)				
Direct effects				
PC food cons.	–0.028*	–0.045**	–0.007	–0.056***
COVID-19	0.230***	–0.003	0.032	0.119***
Indirect effects				
COVID-19 via food cons.	0.003	0.004**	0.001	0.005**
Panel (b)				
Direct effects				
PC caloric intake	0.021	–0.008	–0.000	–0.014
COVID-19	0.240***	–0.001	0.032	0.121***
Indirect effects				
COVID-19 via caloric intake	–0.007	0.003	0.000	0.005
Panel (c)				
Direct effects				
HDDS	0.013	0.020	–0.002	–0.006
COVID-19	0.228***	–0.005	0.033	0.127***
Indirect effects				
COVID-19 via HDDS	0.004	0.007	–0.001	–0.002
Panel (d)				
Direct effects				
Shannon	–0.024*	–0.001	–0.008	–0.004
COVID-19	0.238***	0.002	0.034	0.126***
Indirect effects				
COVID-19 via Shannon	–0.005*	–0.000	–0.002	–0.001
Panel (e)				
Direct effects				
Simpson	–0.022	0.000	–0.009	0.008
COVID-19	0.235***	0.001	0.033	0.125***
Indirect effects				
COVID-19 via Simpson	–0.002	0.00	–0.001	0.001

Note: COVID-19 proxied by a dummy equal to 1 after March 2020 and 0 otherwise. Per capita food consumption and per capita caloric intake have been transformed using the IHS transformation. Household sampling weights applied. Clustered standard errors at the district level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: authors' elaboration based on data from IOF 2019–20.

Concerning the indirect effects of the household food environment on child nutritional outcomes in the context of the COVID-19 crisis, results are mixed. When we look at food consumption, the link is clear: given that COVID-19 led to a reduction in food consumption, which is systematically associated with an increase in child malnutrition, COVID-19 indirectly increased all forms of child malnutrition through a reduction in household food consumption (panel a). This is particularly relevant for wasting and underweight, where the effect is statistically significant. Since the direct effect on the different forms of malnutrition is not significant for other household food environment variables, as a consequence, also the indirect effect does not report a statistically significant coefficient. Regarding the indicators of dietary diversity, we find an opposite result for the Shannon index. Its indirect effect on stunting is negative. This might be because for the sample of children with information on anthropometrics, being in the aftermath of the pandemic is associated with an increase in the Shannon index. Given that the index is negatively correlated with stunting, this indirectly translates into a better outcome.

5.5 Robustness checks

In this section we conduct some tests to assess the robustness of our results. Specifically, we ran three different analyses/tests: (1) a coefficient stability test (Oster 2019) to exclude possible omitted variable bias; (2) Bonferroni and Holm corrections and Romano–Wolf correction to control for family-wise error rate (FWER) when considering the whole family of simultaneous tests instead of treating a single comparison for each outcome; and (3) a sensitivity analysis, where we exclude some provinces considered a possible source of outliers, which could bias the result of the overall sample.

Omitted variable bias

Since we do not have longitudinal data, it is not possible to use fixed effects to control for time-invariant unobserved characteristics that could create problems of endogeneity. Although we included observed controls to reduce the possibility of omitted variable bias, these could be incomplete proxies for the true omitted factor (Oster 2019). It is then important to test if the bias arising from the observed controls is informative about the overall bias, including the unobserved components. Based on the method of Altonji et al. (2005), Oster (2019) developed an approach that combines coefficient stability with information about R-squared movements. With this test, we can examine the extent to which different assumptions regarding omitted variable bias affect our estimates. The test consists of running the full model, with all observed controls, and the restricted one, with only the treatment variable. In our case, as we found the effect of the COVID-19 crisis to occur mostly late in 2020, our variable of interest is the dummy for the third trimester. We then compute consistent estimates of the bias-adjusted treatment effect under two assumptions: a value for the maximum R-squared (Rmax) and a value for the relative degree of selection on observed and unobserved variables (δ). Rmax is equal to 1 when the treatment and the set of controls can fully explain the outcome. When we assume an equal selection relationship between unobservables and observables, meaning that they are equally related to the treatment, δ is equal to 1. We apply different bounding values for Rmax and δ and compare the adjusted β with our original estimate. We consider three different combinations:

1. Rmax = 0.75 and δ=0.5;
2. Rmax = 1 and δ=0.5; and
3. Rmax = 1 and δ=1.

The results of the test show that all adjusted β confirm the sign of the original estimates for all outcome variables (Table 5). Additionally, we can notice that the greater the values of Rmax and δ, the greater the magnitude of the coefficient. This suggests that the original estimates potentially underestimate the real effect.

Table 5: Comparison of original and adjusted estimated coefficients of the dummy of 3rd trimester

	Original beta	Adjusted beta: Rmax = 0.75 and δ = 0.5	Adjusted beta: Rmax = 1 and δ = 0.5	Adjusted beta: Rmax = 0.75 and δ = 1
PC food cons.	–0.243	–0.339	–0.399	–0.554
Caloric intake	-0.368	–1.015	–1.282	–2.195
HDDS	–0.280	–0.388	–0.443	–0.605
Shannon	–0.066	–0.094	–0.108	–0.150
Simpson	–0.026	–0.040	–0.046	–0.066

Note: columns 3–5 report the adjusted coefficient values of a treatment variable based on the proportion of selection derived from observables, based on Oster (2019). Rmax is the theoretical R-squared value from a regression with unobservables included in the main model. δ is the degree of selection on unobservables relative to observables. Household sampling weights applied. Clustered standard errors at the district level. Bootstrapped standard errors, number of replications = 100.

Source: authors' elaboration based on data from IOF 2019–20.

Multiple hypothesis correction

When regressing the effect of a treatment or, as in this case, a shock over a series of outcomes, it is likely to make erroneous inferences due, for instance, to sampling error. Our confidence that a result will generalize to independent data should generally be weaker if it is observed as part of an analysis that involves multiple comparisons, rather than an analysis that involves only a single comparison. In this analysis we have five outcomes at the household level and four outcomes at the child level, which implies nine hypothesis tests. If we just test the hypotheses one by one, then the probability to get one or more false rejections when using a critical value of 0.05 is 23 and 18.5 per cent at household and child levels, respectively. In order to reduce the likelihood of these false rejections, we need to adjust for the fact that we are testing multiple hypotheses. Bonferroni (1935) developed the first technique to account for multiplicity in hypothesis testing, but many other procedures have been implemented over the years. Among them, we use the Romano–Wolf multiple hypothesis correction, described by Romano and Wolf (2005a,b, 2016), to calculate the step-down adjusted *p*-values robust to multiple hypothesis testing. This programme follows the resampling algorithm described by Romano and Wolf (2016) and provides a *p*-value that controls the FWER—that is, the probability of committing any Type I error among all of the hypotheses tested—and allows for dependence among *p*-values by bootstrapping during the resampling process. The Romano–Wolf correction presents many advantages and improvements compared to earlier procedures, including more power and the elimination of the subset pivotality assumption (see Clarke et al. (2020) for a full discussion). We also compute the Holm multiple hypothesis correction and we compare the model *p*-value with the Romano–Wolf and Holm corrections. When correcting for multiple hypothesis testing, the effect of COVID-19, proxied by the dummy of the third trimester, loses significance on the various outcome variables except for stunting, which instead remains significant at the 5 per cent level using both types of correction. The *p*-value for per capita food consumption increases but remains at a low level (around 15 per cent).

Table 6: Multiple hypothesis corrections

Outcome Variable	Model *p*-value	Romano–Wolf *p*-value	Holm *p*-value
PC food consumption	0.000	0.139	0.158
Caloric intake	0.000	0.218	0.475
Shannon index	0.036	0.257	0.495
Simpson index	0.058	0.257	0.257
Stunting	0.002	0.010	0.040
Wasting	0.488	0.812	1.000
Underweight	0.785	0.812	0.753
Overweight	0.251	0.673	0.772

Note: column 2 reports the *p*-value estimated through the original model. Column 3 reports the step-down adjusted *p*-values robust to multiple hypothesis testing, based on the resampling algorithm described by Romano and Wolf (2016). It provides a *p*-value corresponding to the significance of a hypothesis test where S tests have been implemented, providing strong control of the FWER. The algorithm constructs a null distribution for each of the S hypothesis tests based on Studentized bootstrap replications of a subset of the tested variables. Number of replications = 100. Full details of the procedure are described by Romano and Wolf (2016). Column 4 reports the *p*-values corresponding to the Holm multiple hypothesis correction. Household sampling weights applied. Clustered standard errors at the district level.

Source: authors' elaboration based on data from IOF 2019–20.

Sensitivity analysis

Although provinces in Mozambique are quite heterogeneous, two of them are particularly different from the rest of the country. These are the city of Maputo and the province of Cabo Delgado. The first one diverts from the rest of the country because it is the main urban centre, where the economy is much more developed and with the highest level of welfare (70 per cent of households in this province belong to the fifth wealth quintile). In Cabo Delgado a conflict began in October 2017, disrupting many people's livelihoods and forcing people to displace to other areas of the country. As a result, households living in this province are among the poorest in the country (DEEF 2016). Additionally, the ongoing conflict makes data collection difficult, causing possible problems of measurement error. Therefore, the inclusion of these two provinces could falsify the results. To check this we ran the analysis again, excluding each of the two provinces one by one. From the comparison of the original results with the new ones, reported in Figure 15, we can see that the coefficients do not differ substantially. Thus, we conclude that our results are not driven by these specific sample outliers.

Figure 15: Sensitivity analysis excluding provinces of Cabo Delgado and Maputo city

Note: dots are coefficients estimated from a linear regression (first row) and average marginal effects estimated from a probability regression (second row). Household sampling weights applied. Standard errors clustered at the district level. Bars are 95 per cent confidence intervals.

Source: authors' elaboration based on data from IOF 2019–20.

6 Conclusion

This paper aims to understand how COVID-19 has affected food consumption and nutritional outcomes of households and children in Mozambique. The paper provides two main advancements to the current literature. First, it confirms some of the predictions made in previous studies based on simulation exercises. Here, we used real data collected through face-to-face interviews, including physical measurements of weight and height for children under five years old and detailed questions on food consumption. Second, it sheds light on the mechanisms of the effect, looking at the different household and child characteristics and trying to find a link between the household food environment and the child's nutritional status.

We found that after the COVID-19 outbreak, household food consumption and diet quality declined on average. This, however, did not occur immediately, suggesting that, in the beginning, households could rely on different coping mechanisms to offset the negative consequences of the crisis. We also see that a higher stringency level corresponds to a lower caloric intake and food consumption. This result suggests that measures aimed at alleviating food insecurity, such as food and cash transfers, are needed in conjunction with the non-pharmaceutical interventions implemented by the government to counteract the spread of the virus.

From the heterogeneity analysis, we are able to confirm and validate some of the predictions made in previous studies. Specifically, as predicted in Betho et al. (2022), households located in the south have been affected more than households in the rest of the country. In contrast, households that rely on subsistence agriculture were able to offset the negative effects of the shock compared to households involved in other employment sectors. This can be explained by the higher level of enforcement of restrictions in the cities compared to rural villages, and the higher food market dependence. Households in the south, however, were mainly affected in monetary terms. Indeed, they reported a significant reduction only in terms of food consumption. Instead, households practising subsistence agriculture were more effective in terms of dietary diversity and caloric intake than the other households.

Wealthier households are more affected by the COVID-19 crisis in absolute terms, as emerges from the heterogeneity analysis and the quantile regression. This result can be explained through Engel's Law: given that the income elasticity of food consumption is less than 1, the richest households can reduce their food expenditure more than the poorest ones. For the latter, instead, since they were already consuming at the subsistence level, it is much more difficult to shrink their food consumption further when experiencing a negative shock. This result aligns with the simulations by Barletta et al. (2022).

Before the pandemic, the country was already suffering from high levels of stunting, especially in the north, and the COVID-19 crisis further exacerbated this type of malnutrition. This is an alarming trend that cannot be ignored, and immediate actions should be taken. This requires a joint effort by public institutions, including the Ministry of Health, and international organizations operating in the country, such as UNICEF and the World Food Programme (WFP), as well as the involvement of local communities. This is particularly relevant for newborn children, who were most affected. Living in a district with high rates of malnutrition usually is linked to a higher probability that the child is stunted. However, as a consequence of the COVID-19 crisis, children living in other districts are more likely to become stunted.

The mediation analysis showed that the COVID-19 crisis affected child nutrition through the channel of the household food environment proxied by the level of household food consumption. COVID-19 indeed indirectly increased all forms of child malnutrition through a reduction in household food consumption and, in particular, wasting and underweight. However, when considering other proxies for the household food environment, the results are mixed.

Our findings suggest that the households hardest hit by the shock in Mozambique were those located in the south, where the prevalence of stunting is lower, and the wealthiest households whose members were mainly employed in sectors other than agriculture. However, it is worth noting that, although this is the group most affected in absolute terms, the relative effect was found to be higher for poorer households (Barletta et al. 2022).

This is the first paper to look at the consequences of the COVID-19 crisis on food consumption and nutrition in Mozambique, and it is one of the few existing studies that rely on detailed and accurate data on these outcomes during the pandemic. Despite the rich quantity and quality of the information in the data, the type of data itself imposes some limitations on the analysis. Although the coefficient stability test excluded possible endogeneity, we know that this analysis cannot fully isolate the specific impact of COVID-19. Indeed, the nature of the shock and data at hand do not allow using experimental or quasi-experimental models usually employed to measure the impact of exogenous shocks. The COVID-19 shock, given its aggregate and simultaneous nature, cannot fit a typical treatment–control setting. For this reason, we are not able to claim a causal impact of COVID-19 on food consumption and nutrition. However, we are confident that the findings emerging from this analysis have highlighted important patterns and may help steer policy-makers towards better targeted and more effective interventions in the aftermath of this pandemic and the onset of similar undesirable future crises in Mozambique. Better data that can track the same individuals and households over time is needed in the future to assess the impact of shocks in the country more accurately and to monitor the evolution of the effect over time.

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Appendix A

A1 Data description

Variable	Description
Pc Food consumption	Per capita household food expenditure (food purchased + monetary value of food consumed from own production).
Pc Caloric intake	Per capita daily calories consumed in the household.
HDDS	Household Dietary Diversity Score based on 12 food groups.
Simpson index	Simpson dietary diversity index based on 15 food groups. Range [0 : 1].
Shannon index	Shannon dietary diversity index based on 15 food groups. Range [.99 : 3.375].
Stunting	Dummy equal to 1 if height-to-age Z-score$<$2.
Wasting	Dummy equal to 1 if weight-to-height Z-score$<$2.
Underweight	Dummy equal to 1 if weight-to-age Z-score$<$2.
Overweight	Dummy equal to 1 if weight-to-height Z-score$>$2.
HH size	N. of members in the household.
HH head is female	Dummy equal to 1 if the household head is female, zero otherwise.
Asset index	Asset wealth index constructed using principal component analysis based on the DHS approach.
Dep. ratio	Percentage of individuals under 15 and over 64 within the household.
HH has children	Dummy equal to 1 if at least a member of the household is less than 18 years old.
% employed	Percentage of members over 6 years old that worked for at least one hour in the last 7 days, including agricultural activities.
Head has primary educ.	Dummy equal to 1 if household head had completed primary education.
HH owns land	Dummy equal to 1 if household owns a piece of land (machamba).
TLU	N. of Tropical Livestock Units owned by the household.
HH is subsistence ag.	A household is defined to practice subsistence agriculture if the share of food consumption from own production over total food consumption is $>$50%.
Rural	Dummy equal to 1 if household is located in a rural area.
Social assistance	Dummy equal to 1 if household received some social assistance from the government in the last 12 months.
Access to city (hours)	Travel time (in hours) to access the largest cities (>20,000 inhabitants) in the country, based on 500 m resolution raster dataset.
% of land=Savannas	Percentage of land covered by Savannas.
% of land=Grasslands	Percentage of land covered by Grasslands.
% of land=Broadleaf forest	Percentage of land covered by Deciduous Broadleaf forest.
% of land=Urban	Percentage of land covered by Urban and built-up land.

A2 Full regression results

Table A1: Main analysis - Covid-19 dummy, household level

Variables	Per capita food consumption	Per capita Caloric Intake	HDDS	Simpson	Shannon
Covid-19 dummy	-0.243***	-0.368***	-0.337*	-0.0246*	-0.0836***
	(0.0523)	(0.101)	(0.190)	(0.0132)	(0.0300)
HH size	-0.0704***	-0.0533***	0.0662***	-0.00254*	-0.00185
	(0.00496)	(0.00590)	(0.0122)	(0.00153)	(0.00350)
Female headed HH	-0.0735***	-0.00730	-0.175***	-0.00407	-0.0167
	(0.0187)	(0.0282)	(0.0473)	(0.00642)	(0.0144)
Asset index	0.0771***	0.0224**	0.0831***	0.00670***	0.0169***
	(0.00585)	(0.00863)	(0.0195)	(0.00222)	(0.00531)
Dep. Ratio	-0.0544***	-0.0587***	-0.0669***	-0.00983***	-0.0224***
	(0.00960)	(0.0150)	(0.0249)	(0.00310)	(0.00633)
HH with children	-0.213***	-0.119***	0.311***	0.0113	0.0482**
	(0.0273)	(0.0449)	(0.0719)	(0.00858)	(0.0190)
% employed	0.245***	0.138***	0.216**	-0.00649	-0.00577
	(0.0496)	(0.0526)	(0.0993)	(0.0103)	(0.0242)
HH head has primary+ educ.	0.0197	-0.0521*	0.147***	0.0209***	0.0460***
	(0.0172)	(0.0265)	(0.0454)	(0.00634)	(0.0132)
HH owns land	-0.00833	0.0682	-0.0835	0.00944	0.0108
	(0.0305)	(0.0419)	(0.0888)	(0.00922)	(0.0218)
TLUs	-0.000800	0.000813**	0.000795	-7.27e-05	-0.000252
	(0.000690)	(0.000390)	(0.000575)	(7.02e-05)	(0.000153)
HH is subsistence ag.	-0.0144	0.0798	-0.671***	-0.0878***	-0.207***
	(0.0475)	(0.0998)	(0.143)	(0.0121)	(0.0307)
Rural	-0.0168	-0.141*	-0.563***	-0.0190	-0.0571**
	(0.0410)	(0.0727)	(0.106)	(0.0124)	(0.0262)
HH receives social assistence	-0.125***	-0.0975	-0.0509	0.00436	0.0115
	(0.0412)	(0.0648)	(0.103)	(0.0144)	(0.0278)
Access to city (in hours)	0.0151	-0.00116	-0.0613***	-0.00271	-0.00683
	(0.00928)	(0.0146)	(0.0181)	(0.00264)	(0.00522)
% of land=Savannas	-0.00195	-0.00348	-0.00405	-0.000360	-0.00135
	(0.00148)	(0.00224)	(0.00381)	(0.000401)	(0.000933)
% of land=Grasslands	0.000405	0.000344	-0.00114	-0.000658	-0.00169
	(0.00172)	(0.00225)	(0.00424)	(0.000562)	(0.00129)
% of land=Broadleaf forest	0.000610	-0.00423	-0.00478	-0.000335	-0.00196
	(0.00285)	(0.00495)	(0.00739)	(0.000809)	(0.00185)
% of land=Urban	-0.00120	-0.00593*	-0.0172**	-0.00110	-0.00282
	(0.00188)	(0.00335)	(0.00786)	(0.000721)	(0.00172)
prov=CD	0.481***	0.999***	1.978***	0.0334	0.137*
	(0.0831)	(0.0928)	(0.344)	(0.0307)	(0.0787)
prov=NI	-0.165	-0.194	-1.078***	-0.103***	-0.246***
	(0.103)	(0.133)	(0.336)	(0.0318)	(0.0766)
prov=NP	0.259***	0.422***	0.309	0.0307	0.0800
	(0.0817)	(0.121)	(0.285)	(0.0252)	(0.0640)
prov=ZA	0.894***	0.881***	0.814***	-0.130***	-0.218***
	(0.0776)	(0.135)	(0.306)	(0.0301)	(0.0708)
prov=MA	0.109**	-0.108	-0.246	-0.00878	-0.0187
	(0.0456)	(0.0685)	(0.179)	(0.0146)	(0.0374)
prov=SF	-0.0410	0.648***	1.415***	-0.0296	-0.00657
	(0.0843)	(0.0911)	(0.277)	(0.0310)	(0.0767)
prov=IN	0.648***	1.055***	1.469***	-0.0891***	-0.104
	(0.0751)	(0.0907)	(0.294)	(0.0317)	(0.0764)
prov=GZ	0.544***	0.419***	0.793**	-0.00515	0.0340

	(0.0984)	(0.135)	(0.311)	(0.0278)	(0.0679)
prov=MP	0.816***	0.461***	0.242	-0.121***	-0.219***
	(0.0813)	(0.155)	(0.313)	(0.0278)	(0.0673)
prov=MC	0.528***	0.746***	0.785***	-0.0162	-0.0156
	(0.0876)	(0.118)	(0.285)	(0.0302)	(0.0769)
month=February	-0.00176	-0.0661	-0.198	-0.00678	-0.0201
	(0.0546)	(0.0777)	(0.135)	(0.0175)	(0.0384)
month=July	0.281***	0.491***	0.670***	0.0702***	0.196***
	(0.0707)	(0.111)	(0.213)	(0.0194)	(0.0412)
month=August	0.279***	0.462***	0.496**	0.0602***	0.163***
	(0.0691)	(0.116)	(0.225)	(0.0203)	(0.0448)
month=September	0.170**	0.325**	0.466**	0.0513**	0.140***
	(0.0768)	(0.138)	(0.230)	(0.0202)	(0.0456)
month=October	0.189**	0.387***	0.353	0.0281	0.0842*
	(0.0801)	(0.125)	(0.234)	(0.0205)	(0.0449)
month=November	0.225***	0.378***	0.497***	0.0311**	0.0986***
	(0.0461)	(0.0607)	(0.146)	(0.0137)	(0.0304)
month=December	0.139*	0.147*	0.739***	0.0696***	0.173***
	(0.0716)	(0.0870)	(0.151)	(0.0160)	(0.0343)
Constant	4.131***	7.701***	5.616***	0.649***	2.340***
	(0.133)	(0.192)	(0.387)	(0.0461)	(0.110)
Observations	11,836	11,836	11,836	11,836	11,836
R-squared	0.348	0.144	0.261	0.188	0.216

Note: food consumption and caloric intake have been transformed using the inverse hyperbolic sine transformation. Household sampling weights applied. The Covid-19 dummy is a time dummy equal to 1 from July 2020 onwards and 0 otherwise. Regression estimated through a linear model. Clustered standard errors at the district level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Source: authors' elaboration from IOF 2019/2020.

Table A2: Main analysis - Stringency index

Variables	Per capita food consumption	Per capita Caloric Intake	HDDS	Simpson	Shannon
Stringency index	-0.00396***	-0.00599***	-0.00549*	-0.000400*	-0.00136***
	(0.000852)	(0.00164)	(0.00309)	(0.000216)	(0.000489)
HH size	-0.0704***	-0.0533***	0.0662***	-0.00254*	-0.00185
	(0.00496)	(0.00590)	(0.0122)	(0.00153)	(0.00350)
Female headed HH	-0.0735***	-0.00730	-0.175***	-0.00407	-0.0167
	(0.0187)	(0.0282)	(0.0473)	(0.00642)	(0.0144)
Asset index	0.0771***	0.0224**	0.0831***	0.00670***	0.0169***
	(0.00585)	(0.00863)	(0.0195)	(0.00222)	(0.00531)
Dep. Ratio	-0.0544***	-0.0587***	-0.0669***	-0.00983***	-0.0224***
	(0.00960)	(0.0150)	(0.0249)	(0.00310)	(0.00633)
HH with children	-0.213***	-0.119***	0.311***	0.0113	0.0482**
	(0.0273)	(0.0449)	(0.0719)	(0.00858)	(0.0190)
% employed	0.245***	0.138***	0.216**	-0.00649	-0.00577
	(0.0496)	(0.0526)	(0.0993)	(0.0103)	(0.0242)
HH head has primary+ educ.	0.0197	-0.0521*	0.147***	0.0209***	0.0460***
	(0.0172)	(0.0265)	(0.0454)	(0.00634)	(0.0132)
HH owns land	-0.00833	0.0682	-0.0835	0.00944	0.0108
	(0.0305)	(0.0419)	(0.0888)	(0.00922)	(0.0218)
TLUs	-0.000800	0.000813**	0.000795	-7.27e-05	-0.000252
	(0.000690)	(0.000390)	(0.000575)	(7.02e-05)	(0.000153)
HH is subsistence ag.	-0.0144	0.0798	-0.671***	-0.0878***	-0.207***
	(0.0475)	(0.0998)	(0.143)	(0.0121)	(0.0307)
Rural	-0.0168	-0.141*	-0.563***	-0.0190	-0.0571**
	(0.0410)	(0.0727)	(0.106)	(0.0124)	(0.0262)
HH receives social assistence	-0.125***	-0.0975	-0.0509	0.00436	0.0115
	(0.0412)	(0.0648)	(0.103)	(0.0144)	(0.0278)
Access to city (in hours)	0.0151	-0.00116	-0.0613***	-0.00271	-0.00683
	(0.00928)	(0.0146)	(0.0181)	(0.00264)	(0.00522)
% of land=Savannas	-0.00195	-0.00348	-0.00405	-0.000360	-0.00135
	(0.00148)	(0.00224)	(0.00381)	(0.000401)	(0.000933)
% of land=Grasslands	0.000405	0.000344	-0.00114	-0.000658	-0.00169
	(0.00172)	(0.00225)	(0.00424)	(0.000562)	(0.00129)
% of land=Broadleaf forest	0.000610	-0.00423	-0.00478	-0.000335	-0.00196
	(0.00285)	(0.00495)	(0.00739)	(0.000809)	(0.00185)
% of land=Urban	-0.00120	-0.00593*	-0.0172**	-0.00110	-0.00282
	(0.00188)	(0.00335)	(0.00786)	(0.000721)	(0.00172)
prov=CD	0.481***	0.999***	1.978***	0.0334	0.137*
	(0.0831)	(0.0928)	(0.344)	(0.0307)	(0.0787)
prov=NI	-0.165	-0.194	-1.078***	-0.103***	-0.246***
	(0.103)	(0.133)	(0.336)	(0.0318)	(0.0766)
prov=NP	0.259***	0.422***	0.309	0.0307	0.0800
	(0.0817)	(0.121)	(0.285)	(0.0252)	(0.0640)
prov=ZA	0.894***	0.881***	0.814***	-0.130***	-0.218***
	(0.0776)	(0.135)	(0.306)	(0.0301)	(0.0708)
prov=MA	0.109**	-0.108	-0.246	-0.00878	-0.0187
	(0.0456)	(0.0685)	(0.179)	(0.0146)	(0.0374)
prov=SF	-0.0410	0.648***	1.415***	-0.0296	-0.00657
	(0.0843)	(0.0911)	(0.277)	(0.0310)	(0.0767)
prov=IN	0.648***	1.055***	1.469***	-0.0891***	-0.104
	(0.0751)	(0.0907)	(0.294)	(0.0317)	(0.0764)
prov=GZ	0.544***	0.419***	0.793**	-0.00515	0.0340
	(0.0984)	(0.135)	(0.311)	(0.0278)	(0.0679)
prov=MP	0.816***	0.461***	0.242	-0.121***	-0.219***
	(0.0813)	(0.155)	(0.313)	(0.0278)	(0.0673)
prov=MC	0.528***	0.746***	0.785***	-0.0162	-0.0156

	(0.0876)	(0.118)	(0.285)	(0.0302)	(0.0769)
month=February	-0.00176	-0.0661	-0.198	-0.00678	-0.0201
	(0.0546)	(0.0777)	(0.135)	(0.0175)	(0.0384)
month=July	0.322***	0.553***	0.727***	0.0743***	0.210***
	(0.0773)	(0.125)	(0.242)	(0.0209)	(0.0448)
month=August	0.320***	0.524***	0.553**	0.0643***	0.177***
	(0.0759)	(0.130)	(0.254)	(0.0220)	(0.0488)
month=September	0.170**	0.325**	0.466**	0.0513**	0.140***
	(0.0768)	(0.138)	(0.230)	(0.0202)	(0.0456)
month=October	0.189**	0.387***	0.353	0.0281	0.0842*
	(0.0801)	(0.125)	(0.234)	(0.0205)	(0.0449)
month=November	0.225***	0.378***	0.497***	0.0311**	0.0986***
	(0.0461)	(0.0607)	(0.146)	(0.0137)	(0.0304)
month=December	0.139*	0.147*	0.739***	0.0696***	0.173***
	(0.0716)	(0.0870)	(0.151)	(0.0160)	(0.0343)
Constant	4.146***	7.724***	5.637***	0.650***	2.346***
	(0.134)	(0.195)	(0.391)	(0.0463)	(0.111)
Observations	11,836	11,836	11,836	11,836	11,836
R-squared	0.348	0.144	0.261	0.188	0.216

Note: food consumption and caloric intake have been transformed using the inverse hyperbolic sine transformation. Household sampling weights applied. Regression estimated through a linear model. Clustered standard errors at the district level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Source: authors’ elaboration from IOF 2019/2020.

Table A3: Main analysis - Percentage of Covid-19 cases, household level

Variables	Per capita food consumption	Per capita Caloric Intake	HDDS	Simpson	Shannon
Covid-19 cases	-25.20**	-4.110	-41.69	0.0827	-0.519
	(12.27)	(14.63)	(26.09)	(1.711)	(4.919)
HH size	-0.0704***	-0.0534***	0.0663***	-0.00254*	-0.00186
	(0.00496)	(0.00588)	(0.0122)	(0.00153)	(0.00350)
Female headed HH	-0.0737***	-0.00754	-0.175***	-0.00408	-0.0168
	(0.0187)	(0.0283)	(0.0473)	(0.00642)	(0.0144)
Asset index	0.0767***	0.0222**	0.0824***	0.00669***	0.0169***
	(0.00582)	(0.00867)	(0.0195)	(0.00223)	(0.00532)
Dep. Ratio	-0.0545***	-0.0587***	-0.0671***	-0.00983***	-0.0224***
	(0.00961)	(0.0150)	(0.0250)	(0.00310)	(0.00633)
HH with children	-0.214***	-0.119***	0.310***	0.0113	0.0481**
	(0.0273)	(0.0448)	(0.0716)	(0.00857)	(0.0190)
% employed	0.244***	0.137***	0.214**	-0.00653	-0.00594
	(0.0491)	(0.0523)	(0.0988)	(0.0103)	(0.0241)
HH head has primary+ educ.	0.0201	-0.0519*	0.147***	0.0209***	0.0461***
	(0.0172)	(0.0265)	(0.0455)	(0.00634)	(0.0132)
HH owns land	-0.00990	0.0679	-0.0861	0.00944	0.0107
	(0.0305)	(0.0418)	(0.0888)	(0.00923)	(0.0218)
TLUs	-0.000786	0.000819**	0.000818	-7.25e-05	-0.000251
	(0.000694)	(0.000391)	(0.000574)	(7.03e-05)	(0.000153)
HH is subsistence ag.	-0.0150	0.0795	-0.672***	-0.0878***	-0.207***
	(0.0476)	(0.0999)	(0.143)	(0.0121)	(0.0307)
Rural	-0.0175	-0.141*	-0.565***	-0.0190	-0.0571**
	(0.0410)	(0.0727)	(0.106)	(0.0124)	(0.0263)
HH receives social assistence	-0.127***	-0.0980	-0.0535	0.00435	0.0115
	(0.0413)	(0.0647)	(0.103)	(0.0144)	(0.0278)
Access to city (in hours)	0.0152	-0.00115	-0.0612***	-0.00271	-0.00683
	(0.00931)	(0.0146)	(0.0181)	(0.00264)	(0.00522)
% of land=Savannas	-0.00196	-0.00347	-0.00407	-0.000360	-0.00135
	(0.00148)	(0.00223)	(0.00381)	(0.000401)	(0.000932)
% of land=Grasslands	0.000380	0.000341	-0.00118	-0.000657	-0.00170
	(0.00172)	(0.00225)	(0.00424)	(0.000561)	(0.00129)
% of land=Broadleaf forest	0.000567	-0.00422	-0.00485	-0.000334	-0.00195
	(0.00285)	(0.00495)	(0.00739)	(0.000808)	(0.00185)
% of land=Urban	-0.00111	-0.00579*	-0.0171**	-0.00109	-0.00279
	(0.00189)	(0.00334)	(0.00785)	(0.000720)	(0.00172)
prov=CD	0.381***	0.985***	1.812***	0.0340	0.136
	(0.102)	(0.114)	(0.372)	(0.0333)	(0.0866)
prov=NI	-0.267**	-0.207	-1.247***	-0.102***	-0.247***
	(0.118)	(0.145)	(0.364)	(0.0339)	(0.0841)
prov=NP	0.155	0.408***	0.137	0.0313	0.0787
	(0.102)	(0.138)	(0.319)	(0.0278)	(0.0727)
prov=ZA	0.789***	0.867***	0.639*	-0.129***	-0.220***
	(0.100)	(0.150)	(0.343)	(0.0320)	(0.0786)
prov=MA	0.0174	-0.118	-0.399*	-0.00815	-0.0195
	(0.0701)	(0.0901)	(0.223)	(0.0184)	(0.0497)
prov=SF	-0.145	0.635***	1.242***	-0.0290	-0.00792
	(0.0985)	(0.102)	(0.309)	(0.0329)	(0.0834)
prov=IN	0.543***	1.041***	1.295***	-0.0885***	-0.106
	(0.0967)	(0.110)	(0.328)	(0.0338)	(0.0838)
prov=GZ	0.439***	0.405***	0.620*	-0.00457	0.0326
	(0.116)	(0.152)	(0.343)	(0.0303)	(0.0766)
prov=MP	0.712***	0.448***	0.0691	-0.121***	-0.221***
	(0.0992)	(0.160)	(0.344)	(0.0303)	(0.0759)
prov=MC	0.423***	0.732***	0.612*	-0.0156	-0.0170

	(0.108)	(0.134)	(0.321)	(0.0325)	(0.0847)
month=February	-8.07e-05	-0.0657	-0.195	-0.00678	-0.0200
	(0.0544)	(0.0777)	(0.135)	(0.0175)	(0.0384)
month=July	0.0412	0.124*	0.339***	0.0456***	0.113***
	(0.0492)	(0.0674)	(0.0973)	(0.0150)	(0.0304)
month=August	0.0405	0.0948	0.167	0.0356**	0.0795***
	(0.0460)	(0.0651)	(0.108)	(0.0138)	(0.0293)
month=September	-0.0558	-0.0396	0.157	0.0266*	0.0572*
	(0.0616)	(0.107)	(0.129)	(0.0144)	(0.0319)
month=October	-0.0367	0.0223	0.0450	0.00352	0.000938
	(0.0563)	(0.0748)	(0.0964)	(0.0148)	(0.0300)
month=November	0.00919	0.0182	0.205	0.00669	0.0163
	(0.0675)	(0.113)	(0.142)	(0.0173)	(0.0354)
month=December	0.140*	0.147*	0.741***	0.0696***	0.173***
	(0.0715)	(0.0869)	(0.150)	(0.0160)	(0.0343)
Constant	4.233***	7.715***	5.785***	0.648***	2.342***
	(0.140)	(0.183)	(0.400)	(0.0465)	(0.113)
Observations	11,836	11,836	11,836	11,836	11,836
R-squared	0.348	0.144	0.261	0.188	0.216

Note: food consumption and caloric intake have been transformed using the inverse hyperbolic sine transformation. The variable of Covid-19 cases computed by province and by trimester. Household sampling weights applied. Regression estimated through a linear model. Clustered standard errors at the district level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Source: authors' elaboration from IOF 2019/2020.

Table A4: Main analysis - Positivity rate, household level

Variables	Per capita food consumption	Per capita Caloric Intake	HDDS	Simpson	Shannon
Positivity rate	-1.489**	0.0398	-1.978	0.0361	-0.111
	(0.632)	(0.872)	(1.997)	(0.181)	(0.415)
HH size	-0.0705***	-0.0534***	0.0662***	-0.00254*	-0.00187
	(0.00494)	(0.00588)	(0.0122)	(0.00153)	(0.00350)
Female headed HH	-0.0731***	-0.00754	-0.174***	-0.00409	-0.0168
	(0.0187)	(0.0282)	(0.0471)	(0.00641)	(0.0144)
Asset index	0.0768***	0.0223**	0.0827***	0.00669***	0.0169***
	(0.00593)	(0.00870)	(0.0195)	(0.00223)	(0.00532)
Dep. Ratio	-0.0544***	-0.0587***	-0.0669***	-0.00983***	-0.0224***
	(0.00962)	(0.0150)	(0.0249)	(0.00310)	(0.00633)
HH with children	-0.213***	-0.119***	0.311***	0.0113	0.0481**
	(0.0273)	(0.0449)	(0.0716)	(0.00858)	(0.0190)
% employed	0.244***	0.137***	0.215**	-0.00653	-0.00594
	(0.0494)	(0.0523)	(0.0990)	(0.0103)	(0.0242)
HH head has primary+ educ.	0.0205	-0.0520*	0.148***	0.0209***	0.0461***
	(0.0171)	(0.0265)	(0.0454)	(0.00634)	(0.0132)
HH owns land	-0.00801	0.0681	-0.0831	0.00943	0.0108
	(0.0304)	(0.0419)	(0.0889)	(0.00921)	(0.0218)
TLUs	-0.000788	0.000817**	0.000811	-7.27e-05	-0.000250
	(0.000693)	(0.000391)	(0.000574)	(7.02e-05)	(0.000153)
HH is subsistence ag.	-0.0151	0.0796	-0.672***	-0.0878***	-0.207***
	(0.0478)	(0.0999)	(0.143)	(0.0121)	(0.0307)
Rural	-0.0172	-0.141*	-0.564***	-0.0190	-0.0572**
	(0.0412)	(0.0727)	(0.106)	(0.0124)	(0.0262)
HH receives social assistence	-0.125***	-0.0978	-0.0496	0.00432	0.0116
	(0.0413)	(0.0648)	(0.103)	(0.0144)	(0.0278)
Access to city (in hours)	0.0150	-0.00116	-0.0614***	-0.00271	-0.00684
	(0.00929)	(0.0146)	(0.0181)	(0.00264)	(0.00522)
% of land=Savannas	-0.00196	-0.00347	-0.00405	-0.000360	-0.00135
	(0.00148)	(0.00223)	(0.00381)	(0.000401)	(0.000932)
% of land=Grasslands	0.000403	0.000345	-0.00114	-0.000657	-0.00169
	(0.00172)	(0.00225)	(0.00424)	(0.000561)	(0.00129)
% of land=Broadleaf forest	0.000611	-0.00422	-0.00478	-0.000334	-0.00195
	(0.00286)	(0.00495)	(0.00738)	(0.000809)	(0.00185)
% of land=Urban	-0.00115	-0.00578*	-0.0172**	-0.00109	-0.00279
	(0.00189)	(0.00333)	(0.00785)	(0.000720)	(0.00172)
prov=CD	0.394***	1.004***	1.862***	0.0358	0.131*
	(0.0916)	(0.111)	(0.368)	(0.0291)	(0.0744)
prov=NI	-0.213**	-0.188	-1.141***	-0.102***	-0.249***
	(0.105)	(0.136)	(0.352)	(0.0323)	(0.0770)
prov=NP	0.200**	0.427***	0.231	0.0324	0.0763
	(0.0859)	(0.129)	(0.306)	(0.0257)	(0.0639)
prov=ZA	0.816***	0.886***	0.710**	-0.128***	-0.223***
	(0.0881)	(0.149)	(0.340)	(0.0301)	(0.0695)
prov=MA	0.134***	-0.103	-0.213	-0.00898	-0.0160
	(0.0479)	(0.0700)	(0.170)	(0.0148)	(0.0382)
prov=SF	-0.107	0.654***	1.327***	-0.0277	-0.0109
	(0.0843)	(0.0950)	(0.297)	(0.0314)	(0.0756)
prov=IN	0.566***	1.061***	1.360***	-0.0868***	-0.110
	(0.0791)	(0.106)	(0.322)	(0.0316)	(0.0747)
prov=GZ	0.470***	0.425***	0.695**	-0.00309	0.0291
	(0.101)	(0.146)	(0.327)	(0.0289)	(0.0677)
prov=MP	0.755***	0.467***	0.160	-0.120***	-0.223***
	(0.0855)	(0.159)	(0.334)	(0.0289)	(0.0679)
prov=MC	0.483***	0.751***	0.725**	-0.0148	-0.0184

	(0.0906)	(0.126)	(0.295)	(0.0299)	(0.0752)
month=February	-0.000350	-0.0660	-0.196	-0.00681	-0.0199
	(0.0547)	(0.0779)	(0.135)	(0.0175)	(0.0385)
month=July	0.121*	0.121	0.445***	0.0436**	0.119***
	(0.0656)	(0.0938)	(0.160)	(0.0201)	(0.0425)
month=August	0.119*	0.0918	0.269	0.0336*	0.0855**
	(0.0613)	(0.0932)	(0.175)	(0.0198)	(0.0427)
month=September	0.00999	-0.0446	0.239	0.0247	0.0630
	(0.0767)	(0.131)	(0.186)	(0.0192)	(0.0433)
month=October	0.0294	0.0173	0.127	0.00155	0.00679
	(0.0681)	(0.0869)	(0.163)	(0.0200)	(0.0430)
month=November	0.0704	0.0117	0.278	0.00467	0.0222
	(0.0802)	(0.136)	(0.172)	(0.0210)	(0.0430)
month=December	0.142**	0.147*	0.742***	0.0695***	0.173***
	(0.0715)	(0.0871)	(0.150)	(0.0160)	(0.0343)
Constant	4.186***	7.696***	5.689***	0.647***	2.344***
	(0.134)	(0.189)	(0.404)	(0.0463)	(0.111)
Observations	11,836	11,836	11,836	11,836	11,836
R-squared	0.348	0.144	0.261	0.188	0.216

Note: food consumption and caloric intake have been transformed using the inverse hyperbolic sine transformation. The positivity rate is the percentage of Covid-19 cases over tests, by province and by trimester. Household sampling weights applied. Regression estimated through a linear model. Clustered standard errors at the district level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Source: authors' elaboration from IOF 2019/2020.

Table A5: Main analysis - Trimesters, household level

Variables	**Per capita food consumption**	**Per capita Caloric Intake**	**HDDS**	**Simpson**	**Shannon**
2nd Trimester	0.0373	0.123*	0.333***	0.0456***	0.113***
	(0.0491)	(0.0671)	(0.0976)	(0.0149)	(0.0303)
3rd Trimester	-0.243***	-0.368***	-0.337*	-0.0246*	-0.0836***
	(0.0523)	(0.101)	(0.190)	(0.0132)	(0.0300)
HH size	-0.0704***	-0.0533***	0.0662***	-0.00254*	-0.00185
	(0.00496)	(0.00590)	(0.0122)	(0.00153)	(0.00350)
Female headed HH	-0.0735***	-0.00730	-0.175***	-0.00407	-0.0167
	(0.0187)	(0.0282)	(0.0473)	(0.00642)	(0.0144)
Asset index	0.0771***	0.0224**	0.0831***	0.00670***	0.0169***
	(0.00585)	(0.00863)	(0.0195)	(0.00222)	(0.00531)
Dep. Ratio	-0.0544***	-0.0587***	-0.0669***	-0.00983***	-0.0224***
	(0.00960)	(0.0150)	(0.0249)	(0.00310)	(0.00633)
HH with children	-0.213***	-0.119***	0.311***	0.0113	0.0482**
	(0.0273)	(0.0449)	(0.0719)	(0.00858)	(0.0190)
% employed	0.245***	0.138***	0.216**	-0.00649	-0.00577
	(0.0496)	(0.0526)	(0.0993)	(0.0103)	(0.0242)
HH head has primary+ educ.	0.0197	-0.0521*	0.147***	0.0209***	0.0460***
	(0.0172)	(0.0265)	(0.0454)	(0.00634)	(0.0132)
HH owns land	-0.00833	0.0682	-0.0835	0.00944	0.0108
	(0.0305)	(0.0419)	(0.0888)	(0.00922)	(0.0218)
TLUs	-0.000800	0.000813**	0.000795	-7.27e-05	-0.000252
	(0.000690)	(0.000390)	(0.000575)	(7.02e-05)	(0.000153)
HH is subsistence ag.	-0.0144	0.0798	-0.671***	-0.0878***	-0.207***
	(0.0475)	(0.0998)	(0.143)	(0.0121)	(0.0307)
Rural	-0.0168	-0.141*	-0.563***	-0.0190	-0.0571**
	(0.0410)	(0.0727)	(0.106)	(0.0124)	(0.0262)
HH receives social assistence	-0.125***	-0.0975	-0.0509	0.00436	0.0115
	(0.0412)	(0.0648)	(0.103)	(0.0144)	(0.0278)
Access to city (in hours)	0.0151	-0.00116	-0.0613***	-0.00271	-0.00683
	(0.00928)	(0.0146)	(0.0181)	(0.00264)	(0.00522)
% of land=Savannas	-0.00195	-0.00348	-0.00405	-0.000360	-0.00135
	(0.00148)	(0.00224)	(0.00381)	(0.000401)	(0.000933)
% of land=Grasslands	0.000405	0.000344	-0.00114	-0.000658	-0.00169
	(0.00172)	(0.00225)	(0.00424)	(0.000562)	(0.00129)
% of land=Broadleaf forest	0.000610	-0.00423	-0.00478	-0.000335	-0.00196
	(0.00285)	(0.00495)	(0.00739)	(0.000809)	(0.00185)
% of land=Urban	-0.00120	-0.00593*	-0.0172**	-0.00110	-0.00282
	(0.00188)	(0.00335)	(0.00786)	(0.000721)	(0.00172)
prov=CD	0.481***	0.999***	1.978***	0.0334	0.137*
	(0.0831)	(0.0928)	(0.344)	(0.0307)	(0.0787)
prov=NI	-0.165	-0.194	-1.078***	-0.103***	-0.246***
	(0.103)	(0.133)	(0.336)	(0.0318)	(0.0766)
prov=NP	0.259***	0.422***	0.309	0.0307	0.0800
	(0.0817)	(0.121)	(0.285)	(0.0252)	(0.0640)
prov=ZA	0.894***	0.881***	0.814***	-0.130***	-0.218***
	(0.0776)	(0.135)	(0.306)	(0.0301)	(0.0708)
prov=MA	0.109**	-0.108	-0.246	-0.00878	-0.0187
	(0.0456)	(0.0685)	(0.179)	(0.0146)	(0.0374)
prov=SF	-0.0410	0.648***	1.415***	-0.0296	-0.00657
	(0.0843)	(0.0911)	(0.277)	(0.0310)	(0.0767)
prov=IN	0.648***	1.055***	1.469***	-0.0891***	-0.104
	(0.0751)	(0.0907)	(0.294)	(0.0317)	(0.0764)
prov=GZ	0.544***	0.419***	0.793**	-0.00515	0.0340
	(0.0984)	(0.135)	(0.311)	(0.0278)	(0.0679)
prov=MP	0.816***	0.461***	0.242	-0.121***	-0.219***

	(0.0813)	(0.155)	(0.313)	(0.0278)	(0.0673)
prov=MC	0.528***	0.746***	0.785***	-0.0162	-0.0156
	(0.0876)	(0.118)	(0.285)	(0.0302)	(0.0769)
month=February	-0.00176	-0.0661	-0.198	-0.00678	-0.0201
	(0.0546)	(0.0777)	(0.135)	(0.0175)	(0.0384)
month=August	-0.00140	-0.0294	-0.174	-0.00996	-0.0332
	(0.0452)	(0.0565)	(0.114)	(0.0123)	(0.0268)
month=September	0.170**	0.325**	0.466**	0.0513**	0.140***
	(0.0768)	(0.138)	(0.230)	(0.0202)	(0.0456)
month=October	0.189**	0.387***	0.353	0.0281	0.0842*
	(0.0801)	(0.125)	(0.234)	(0.0205)	(0.0449)
month=November	0.225***	0.378***	0.497***	0.0311**	0.0986***
	(0.0461)	(0.0607)	(0.146)	(0.0137)	(0.0304)
month=December	0.139*	0.147*	0.739***	0.0696***	0.173***
	(0.0716)	(0.0870)	(0.151)	(0.0160)	(0.0343)
Constant	4.131***	7.701***	5.616***	0.649***	2.340***
	(0.133)	(0.192)	(0.387)	(0.0461)	(0.110)
Observations	11,836	11,836	11,836	11,836	11,836
R-squared	0.348	0.144	0.261	0.188	0.216

Note: food consumption and caloric intake have been transformed using the inverse hyperbolic sine transformation. Household sampling weights applied. Regression estimated through a linear model. Clustered standard errors at the district level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Source: authors' elaboration from IOF 2019/2020.

Table A6: Heterogeneity analysis - Household level, rural vs urban

Variables	**Per capita food consumption**	**Per capita Caloric Intake**	**HDDS**	**Simpson**	**Shannon**
2nd Trimester	0.00579	0.0705	0.260**	0.0299*	0.0936***
	(0.0679)	(0.0731)	(0.129)	(0.0165)	(0.0329)
3rd Trimester	-0.237***	-0.326***	-0.370*	-0.0272**	-0.0865***
	(0.0507)	(0.0915)	(0.207)	(0.0134)	(0.0317)
2nd Trimester*Rural	0.0495	0.0825	0.115	0.0248	0.0299
	(0.0714)	(0.0939)	(0.157)	(0.0194)	(0.0400)
3rd Trimester*Rural	0.00888	-0.0775	0.166	0.0221	0.0254
	(0.0732)	(0.0965)	(0.156)	(0.0190)	(0.0415)
HH size	-0.0704***	-0.0534***	0.0663***	-0.00254*	-0.00185
	(0.00496)	(0.00588)	(0.0122)	(0.00152)	(0.00349)
Female headed HH	-0.0734***	-0.00670	-0.175***	-0.00410	-0.0168
	(0.0187)	(0.0282)	(0.0474)	(0.00642)	(0.0144)
Asset index	0.0768***	0.0216**	0.0831***	0.00663***	0.0169***
	(0.00593)	(0.00860)	(0.0198)	(0.00224)	(0.00535)
Dep. Ratio	-0.0541***	-0.0576***	-0.0672***	-0.00979***	-0.0224***
	(0.00960)	(0.0150)	(0.0252)	(0.00309)	(0.00632)
HH with children	-0.213***	-0.119***	0.309***	0.0109	0.0477**
	(0.0274)	(0.0450)	(0.0718)	(0.00854)	(0.0189)
% employed	0.245***	0.138***	0.214**	-0.00663	-0.00593
	(0.0496)	(0.0525)	(0.0988)	(0.0103)	(0.0242)
HH head has primary educ.	0.0197	-0.0520*	0.147***	0.0209***	0.0460***
	(0.0171)	(0.0265)	(0.0454)	(0.00632)	(0.0132)
HH owns land	-0.00951	0.0638	-0.0824	0.00931	0.0106
	(0.0304)	(0.0418)	(0.0894)	(0.00913)	(0.0216)
TLUs	-0.000805	0.000835**	0.000737	-8.09e-05	-0.000261*
	(0.000690)	(0.000389)	(0.000581)	(6.99e-05)	(0.000153)
HH is subsistence ag.	-0.0142	0.0812	-0.673***	-0.0879***	-0.207***
	(0.0478)	(0.100)	(0.144)	(0.0121)	(0.0307)
Rural	-0.0384	-0.144	-0.666***	-0.0363**	-0.0775**
	(0.0651)	(0.0892)	(0.149)	(0.0163)	(0.0351)
HH receives social assistence	-0.126***	-0.0982	-0.0509	0.00430	0.0115
	(0.0413)	(0.0649)	(0.103)	(0.0145)	(0.0279)
Access to city (in hours)	0.0150	-0.00127	-0.0613***	-0.00273	-0.00685
	(0.00929)	(0.0145)	(0.0182)	(0.00261)	(0.00520)
% of land=Savannas	-0.00199	-0.00355	-0.00410	-0.000373	-0.00137
	(0.00149)	(0.00221)	(0.00380)	(0.000404)	(0.000936)
% of land=Grasslands	0.000393	0.000316	-0.00116	-0.000663	-0.00170
	(0.00174)	(0.00221)	(0.00422)	(0.000567)	(0.00129)
% of land=Broadleaf forest	0.000573	-0.00429	-0.00488	-0.000356	-0.00198
	(0.00287)	(0.00491)	(0.00738)	(0.000815)	(0.00186)
% of land=Urban	-0.00128	-0.00616*	-0.0172**	-0.00112	-0.00284
	(0.00190)	(0.00332)	(0.00793)	(0.000729)	(0.00174)
prov=CD	0.482***	1.002***	1.979***	0.0338	0.138*
	(0.0832)	(0.0906)	(0.346)	(0.0308)	(0.0788)
prov=NI	-0.165	-0.192	-1.081***	-0.103***	-0.246***
	(0.103)	(0.131)	(0.338)	(0.0318)	(0.0767)
prov=NP	0.259***	0.423***	0.308	0.0305	0.0799
	(0.0822)	(0.120)	(0.286)	(0.0253)	(0.0642)
prov=ZA	0.893***	0.877***	0.814***	-0.130***	-0.218***
	(0.0779)	(0.132)	(0.307)	(0.0304)	(0.0713)
prov=MA	0.109**	-0.111*	-0.245	-0.00887	-0.0188
	(0.0458)	(0.0663)	(0.180)	(0.0146)	(0.0375)
prov=SF	-0.0409	0.650***	1.413***	-0.0299	-0.00686
	(0.0844)	(0.0883)	(0.278)	(0.0312)	(0.0770)
prov=IN	0.648***	1.054***	1.468***	-0.0892***	-0.104
	(0.0752)	(0.0891)	(0.296)	(0.0318)	(0.0766)

prov=GZ	0.543***	0.419***	0.789**	-0.00579	0.0332
	(0.0989)	(0.133)	(0.313)	(0.0279)	(0.0683)
prov=MP	0.815***	0.460***	0.239	-0.122***	-0.220***
	(0.0814)	(0.153)	(0.314)	(0.0279)	(0.0675)
prov=MC	0.527***	0.745***	0.782***	-0.0167	-0.0162
	(0.0878)	(0.116)	(0.287)	(0.0304)	(0.0774)
month=February	-0.000240	-0.0664	-0.190	-0.00548	-0.0185
	(0.0551)	(0.0784)	(0.136)	(0.0173)	(0.0383)
month=August	-0.00253	-0.0328	-0.174	-0.0102	-0.0336
	(0.0453)	(0.0565)	(0.113)	(0.0123)	(0.0268)
month=September	0.158**	0.333**	0.394*	0.0399**	0.127***
	(0.0774)	(0.129)	(0.213)	(0.0195)	(0.0427)
month=October	0.178**	0.399***	0.279	0.0166	0.0707*
	(0.0859)	(0.128)	(0.223)	(0.0199)	(0.0423)
month=November	0.213***	0.385***	0.427***	0.0199	0.0855***
	(0.0526)	(0.0604)	(0.144)	(0.0135)	(0.0304)
month=December	0.139*	0.147*	0.739***	0.0695***	0.173***
	(0.0716)	(0.0869)	(0.152)	(0.0159)	(0.0342)
Constant	4.149***	7.710***	5.689***	0.661***	2.356***
	(0.139)	(0.185)	(0.392)	(0.0481)	(0.113)
Observations	11,836	11,836	11,836	11,836	11,836
R-squared	0.348	0.145	0.261	0.189	0.216

Note: food consumption and caloric intake have been transformed using the inverse hyperbolic sine transformation. Household sampling weights applied. Regression estimated through a linear model. Clustered standard errors at the district level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Source: authors' elaboration from IOF 2019/2020.

Table A7: Heterogeneity analysis - Household level, geographic area

Variables	**Per capita food consumption**	**Per capita Caloric Intake**	**HDDS**	**Simpson**	**Shannon**
2nd Trimester	0.0948	0.0598	0.254**	0.0505**	0.114***
	(0.0579)	(0.0836)	(0.116)	(0.0199)	(0.0406)
3rd Trimester	-0.0800	-0.418***	-0.243	-0.0215	-0.0905*
	(0.0860)	(0.153)	(0.200)	(0.0212)	(0.0462)
2nd Trimester*Center	-0.0303	0.210	0.437**	-0.00863	0.0101
	(0.0949)	(0.128)	(0.215)	(0.0271)	(0.0575)
2nd Trimester*South	-0.223***	0.0528	-0.128	-0.0128	-0.0181
	(0.0705)	(0.0943)	(0.165)	(0.0195)	(0.0416)
3rd Trimester*Center	0.0251	0.149	0.346*	0.00738	0.0336
	(0.0918)	(0.146)	(0.199)	(0.0251)	(0.0549)
3rd Trimester*South	-0.187**	0.0514	-0.124	-0.00417	0.00693
	(0.0719)	(0.105)	(0.163)	(0.0176)	(0.0399)
Center	0.411***	-0.238	-1.430***	-0.163***	-0.371***
	(0.0837)	(0.146)	(0.258)	(0.0268)	(0.0607)
South	-0.331***	-1.035***	-1.881***	-0.0271	-0.132*
	(0.0963)	(0.121)	(0.371)	(0.0306)	(0.0790)
HH size	-0.0707***	-0.0535***	0.0656***	-0.00254*	-0.00187
	(0.00494)	(0.00590)	(0.0123)	(0.00153)	(0.00351)
Female headed HH	-0.0731***	-0.00701	-0.173***	-0.00406	-0.0167
	(0.0188)	(0.0284)	(0.0473)	(0.00643)	(0.0144)
Asset index	0.0767***	0.0221**	0.0819***	0.00671***	0.0170***
	(0.00599)	(0.00864)	(0.0195)	(0.00223)	(0.00530)
Dep. Ratio	-0.0536***	-0.0583***	-0.0651***	-0.00982***	-0.0224***
	(0.00967)	(0.0150)	(0.0249)	(0.00310)	(0.00634)
HH with children	-0.212***	-0.115**	0.320***	0.0113	0.0488**
	(0.0272)	(0.0448)	(0.0710)	(0.00853)	(0.0189)
% employed	0.248***	0.145***	0.234**	-0.00644	-0.00488
	(0.0488)	(0.0526)	(0.0973)	(0.0102)	(0.0239)
HH head has primary educ.	0.0204	-0.0514*	0.149***	0.0208***	0.0459***
	(0.0171)	(0.0265)	(0.0455)	(0.00636)	(0.0133)
HH owns land	-0.00781	0.0666	-0.0861	0.00941	0.0104
	(0.0304)	(0.0419)	(0.0888)	(0.00920)	(0.0217)
TLUs	-0.000772	0.000880**	0.000977	-7.21e-05	-0.000244
	(0.000687)	(0.000395)	(0.000599)	(7.14e-05)	(0.000155)
HH is subsistence ag.	-0.0168	0.0802	-0.673***	-0.0880***	-0.207***
	(0.0482)	(0.0995)	(0.142)	(0.0122)	(0.0306)
Rural	-0.0189	-0.146**	-0.577***	-0.0187	-0.0570**
	(0.0410)	(0.0728)	(0.106)	(0.0124)	(0.0262)
HH receives social assistence	-0.122***	-0.0951	-0.0425	0.00455	0.0123
	(0.0407)	(0.0650)	(0.102)	(0.0144)	(0.0279)
Access to city (in hours)	0.0156	-0.000112	-0.0584***	-0.00265	-0.00663
	(0.00951)	(0.0150)	(0.0187)	(0.00264)	(0.00524)
% of land=Savannas	-0.00195	-0.00357	-0.00424	-0.000359	-0.00136
	(0.00148)	(0.00224)	(0.00381)	(0.000399)	(0.000930)
% of land=Grasslands	0.000410	0.000272	-0.00130	-0.000655	-0.00170
	(0.00171)	(0.00223)	(0.00424)	(0.000558)	(0.00128)
% of land=Broadleaf forest	0.000581	-0.00444	-0.00529	-0.000330	-0.00197
	(0.00285)	(0.00493)	(0.00742)	(0.000806)	(0.00185)
% of land=Urban	-0.00119	-0.00597*	-0.0173**	-0.00110	-0.00285
	(0.00190)	(0.00341)	(0.00786)	(0.000727)	(0.00173)
prov=NI	-0.172*	-0.194	-1.084***	-0.104***	-0.248***
	(0.104)	(0.133)	(0.337)	(0.0319)	(0.0767)
prov=NP	0.254***	0.423***	0.308	0.0303	0.0791
	(0.0805)	(0.122)	(0.284)	(0.0251)	(0.0638)
prov=MA	0.109**	-0.105	-0.241	-0.00888	-0.0189
	(0.0456)	(0.0680)	(0.179)	(0.0145)	(0.0373)

prov=SF	-0.526***	-0.346***	-0.556***	-0.0632***	-0.143**
	(0.0653)	(0.0939)	(0.167)	(0.0232)	(0.0557)
prov=IN	0.161***	0.0585	-0.509***	-0.123***	-0.241***
	(0.0507)	(0.0622)	(0.185)	(0.0265)	(0.0603)
prov=GZ	-0.351***	-0.464***	-0.0277	0.125***	0.252***
	(0.0671)	(0.144)	(0.198)	(0.0205)	(0.0362)
prov=MP	-0.0777	-0.429**	-0.592***	0.00882	-0.00173
	(0.0622)	(0.170)	(0.221)	(0.0243)	(0.0461)
prov=MC	0.0423	-0.247**	-1.184***	-0.0499**	-0.152***
	(0.0665)	(0.0984)	(0.177)	(0.0229)	(0.0569)
month=February	-0.00101	-0.0688	-0.203	-0.00676	-0.0204
	(0.0536)	(0.0768)	(0.131)	(0.0174)	(0.0381)
month=August	-0.00513	-0.0273	-0.172	-0.0104	-0.0339
	(0.0448)	(0.0576)	(0.112)	(0.0123)	(0.0267)
month=September	0.0414	0.327**	0.311	0.0474**	0.138***
	(0.0797)	(0.143)	(0.200)	(0.0205)	(0.0448)
month=October	0.0619	0.389***	0.201	0.0245	0.0820*
	(0.0840)	(0.142)	(0.210)	(0.0201)	(0.0433)
month=November	0.107**	0.375***	0.350***	0.0264*	0.0920***
	(0.0503)	(0.0661)	(0.129)	(0.0137)	(0.0313)
month=December	0.142**	0.145*	0.738***	0.0697***	0.173***
	(0.0713)	(0.0863)	(0.148)	(0.0160)	(0.0345)
Constant	4.580***	8.740***	7.642***	0.680***	2.480***
	(0.160)	(0.237)	(0.463)	(0.0479)	(0.114)
Observations	11,836	11,836	11,836	11,836	11,836
R-squared	0.350	0.145	0.263	0.189	0.216

Note: food consumption and caloric intake have been transformed using the inverse hyperbolic sine transformation. Household sampling weights applied. Regression estimated through a linear model. Clustered standard errors at the district level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Source: authors' elaboration from IOF 2019/2020.

Table A8: Heterogeneity analysis - Household level, education of household head

Variables	**Per capita food consumption**	**Per capita Caloric Intake**	**HDDS**	**Simpson**	**Shannon**
2nd Trimester	0.0308	0.137*	0.278**	0.0417**	0.0930**
	(0.0547)	(0.0784)	(0.107)	(0.0184)	(0.0372)
3rd Trimester	-0.228***	-0.385***	-0.241	-0.0295*	-0.103***
	(0.0649)	(0.122)	(0.200)	(0.0162)	(0.0358)
2nd Trimester* Primary+ educ. of HH head	0.0126	-0.0277	0.108	0.00798	0.0402
	(0.0454)	(0.0626)	(0.109)	(0.0133)	(0.0283)
3rd Trimester* Primary+ educ. of HH head	-0.0236	0.0274	-0.148	0.00606	0.0229
	(0.0489)	(0.0808)	(0.108)	(0.0115)	(0.0250)
HH size	-0.0703***	-0.0534***	0.0668***	-0.00254*	-0.00186
	(0.00500)	(0.00587)	(0.0123)	(0.00153)	(0.00351)
Female headed HH	-0.0734***	-0.00740	-0.174***	-0.00409	-0.0168
	(0.0187)	(0.0282)	(0.0473)	(0.00642)	(0.0144)
Asset index	0.0771***	0.0225**	0.0828***	0.00671***	0.0170***
	(0.00587)	(0.00867)	(0.0195)	(0.00222)	(0.00529)
Dep. Ratio	-0.0544***	-0.0586***	-0.0672***	-0.00984***	-0.0225***
	(0.00961)	(0.0150)	(0.0248)	(0.00310)	(0.00633)
HH with children	-0.213***	-0.119***	0.312***	0.0113	0.0483**
	(0.0272)	(0.0449)	(0.0718)	(0.00859)	(0.0191)
% employed	0.245***	0.138***	0.217**	-0.00656	-0.00605
	(0.0495)	(0.0527)	(0.0987)	(0.0104)	(0.0243)
HH head has primary+ educ.	0.0244	-0.0528	0.165**	0.0158	0.0230
	(0.0344)	(0.0498)	(0.0834)	(0.0103)	(0.0228)
HH owns land	-0.00785	0.0674	-0.0799	0.00955	0.0114
	(0.0304)	(0.0419)	(0.0888)	(0.00921)	(0.0217)
TLUs	-0.000805	0.000817**	0.000769	-7.05e-05	-0.000243
	(0.000689)	(0.000390)	(0.000577)	(6.98e-05)	(0.000152)
HH is subsistence ag.	-0.0141	0.0791	-0.669***	-0.0876***	-0.206***
	(0.0477)	(0.100)	(0.143)	(0.0120)	(0.0305)
Rural	-0.0173	-0.140*	-0.567***	-0.0190	-0.0576**
	(0.0410)	(0.0724)	(0.105)	(0.0123)	(0.0260)
HH receives social assistence	-0.126***	-0.0963	-0.0562	0.00429	0.0110
	(0.0413)	(0.0649)	(0.103)	(0.0144)	(0.0278)
Access to city (in hours)	0.0150	-0.00101	-0.0620***	-0.00272	-0.00690
	(0.00930)	(0.0146)	(0.0180)	(0.00264)	(0.00520)
% of land=Savannas	-0.00195	-0.00348	-0.00402	-0.000362	-0.00136
	(0.00148)	(0.00224)	(0.00381)	(0.000401)	(0.000933)
% of land=Grasslands	0.000412	0.000338	-0.00110	-0.000661	-0.00171
	(0.00172)	(0.00225)	(0.00424)	(0.000562)	(0.00129)
% of land=Broadleaf forest	0.000616	-0.00424	-0.00474	-0.000339	-0.00197
	(0.00285)	(0.00496)	(0.00736)	(0.000810)	(0.00185)
% of land=Urban	-0.00118	-0.00597*	-0.0170**	-0.00110	-0.00279
	(0.00188)	(0.00334)	(0.00788)	(0.000722)	(0.00173)
prov=CD	0.480***	1.000***	1.972***	0.0337	0.138*
	(0.0834)	(0.0932)	(0.346)	(0.0307)	(0.0788)
prov=NI	-0.166	-0.193	-1.082***	-0.103***	-0.245***
	(0.103)	(0.133)	(0.338)	(0.0318)	(0.0767)
prov=NP	0.258***	0.422***	0.307	0.0309	0.0808
	(0.0818)	(0.121)	(0.287)	(0.0252)	(0.0641)
prov=ZA	0.895***	0.880***	0.819***	-0.130***	-0.217***
	(0.0776)	(0.135)	(0.307)	(0.0302)	(0.0711)
prov=MA	0.109**	-0.108	-0.246	-0.00858	-0.0178
	(0.0454)	(0.0684)	(0.180)	(0.0146)	(0.0375)
prov=SF	-0.0418	0.649***	1.411***	-0.0294	-0.00565

	(0.0843)	(0.0901)	(0.278)	(0.0310)	(0.0767)
prov=IN	0.647***	1.055***	1.466***	-0.0889***	-0.104
	(0.0754)	(0.0906)	(0.295)	(0.0317)	(0.0765)
prov=GZ	0.543***	0.420***	0.790**	-0.00478	0.0356
	(0.0988)	(0.136)	(0.312)	(0.0278)	(0.0682)
prov=MP	0.816***	0.461***	0.241	-0.121***	-0.218***
	(0.0815)	(0.155)	(0.314)	(0.0279)	(0.0675)
prov=MC	0.527***	0.746***	0.783***	-0.0161	-0.0151
	(0.0879)	(0.118)	(0.287)	(0.0302)	(0.0769)
month=February	-0.00181	-0.0662	-0.198	-0.00664	-0.0194
	(0.0547)	(0.0779)	(0.136)	(0.0175)	(0.0385)
month=August	-0.00143	-0.0293	-0.174	-0.00996	-0.0332
	(0.0451)	(0.0566)	(0.113)	(0.0123)	(0.0267)
month=September	0.166**	0.329**	0.440*	0.0533***	0.149***
	(0.0756)	(0.136)	(0.229)	(0.0201)	(0.0449)
month=October	0.185**	0.391***	0.329	0.0302	0.0930**
	(0.0782)	(0.126)	(0.233)	(0.0203)	(0.0442)
month=November	0.222***	0.380***	0.485***	0.0331**	0.107***
	(0.0463)	(0.0618)	(0.146)	(0.0134)	(0.0297)
month=December	0.139*	0.147*	0.738***	0.0699***	0.175***
	(0.0718)	(0.0879)	(0.151)	(0.0160)	(0.0345)
Constant	4.128***	7.703***	5.602***	0.651***	2.351***
	(0.134)	(0.196)	(0.388)	(0.0467)	(0.112)
Observations	11,836	11,836	11,836	11,836	11,836
R-squared	0.348	0.144	0.262	0.188	0.216

Note: food consumption and caloric intake have been transformed using the inverse hyperbolic sine transformation. Household sampling weights applied. Regression estimated through a linear model. Clustered standard errors at the district level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Source: authors' elaboration from IOF 2019/2020.

Table A9: Heterogeneity analysis- Household level, HHs with/no children

Variables	**Per capita food consumption**	**Per capita Caloric Intake**	**HDDS**	**Simpson**	**Shannon**
2nd Trimester	0.0764	0.226**	0.373**	0.0530**	0.133***
	(0.0674)	(0.0918)	(0.150)	(0.0204)	(0.0451)
3rd Trimester	-0.266***	-0.403***	-0.354*	-0.0337*	-0.111***
	(0.0663)	(0.130)	(0.201)	(0.0185)	(0.0423)
2nd Trimester* HH with children	-0.0458	-0.120	-0.0466	-0.00870	-0.0233
	(0.0616)	(0.0857)	(0.149)	(0.0165)	(0.0392)
3rd Trimester* HH with children	0.0257	0.0338	0.0171	0.0112	0.0332
	(0.0690)	(0.126)	(0.174)	(0.0198)	(0.0443)
HH size	-0.0704***	-0.0533***	0.0663***	-0.00253	-0.00183
	(0.00496)	(0.00593)	(0.0122)	(0.00153)	(0.00351)
Female headed HH	-0.0733***	-0.00678	-0.174***	-0.00403	-0.0166
	(0.0187)	(0.0282)	(0.0475)	(0.00642)	(0.0144)
Asset index	0.0770***	0.0222**	0.0830***	0.00667***	0.0169***
	(0.00581)	(0.00856)	(0.0195)	(0.00221)	(0.00526)
Dep. Ratio	-0.0545***	-0.0590***	-0.0671***	-0.00985***	-0.0225***
	(0.00967)	(0.0152)	(0.0251)	(0.00311)	(0.00636)
HH with children	-0.206***	-0.0886	0.321**	0.0102	0.0440
	(0.0487)	(0.0710)	(0.135)	(0.0170)	(0.0389)
% employed	0.245***	0.138**	0.216**	-0.00637	-0.00543
	(0.0496)	(0.0531)	(0.0991)	(0.0103)	(0.0241)
HH head has primary+ educ.	0.0195	-0.0524**	0.147***	0.0208***	0.0458***
	(0.0171)	(0.0264)	(0.0456)	(0.00635)	(0.0133)
HH owns land	-0.00839	0.0680	-0.0836	0.00943	0.0108
	(0.0305)	(0.0419)	(0.0891)	(0.00926)	(0.0219)
TLUs	-0.000799	0.000813**	0.000795	-7.21e-05	-0.000250
	(0.000690)	(0.000390)	(0.000576)	(7.05e-05)	(0.000154)
HH is subsistence ag.	-0.0147	0.0792	-0.672***	-0.0878***	-0.207***
	(0.0473)	(0.0995)	(0.143)	(0.0120)	(0.0305)
Rural	-0.0170	-0.141*	-0.564***	-0.0191	-0.0574**
	(0.0407)	(0.0724)	(0.106)	(0.0124)	(0.0263)
HH receives social assistence	-0.125***	-0.0973	-0.0508	0.00437	0.0116
	(0.0412)	(0.0646)	(0.103)	(0.0144)	(0.0278)
Access to city (in hours)	0.0150	-0.00126	-0.0613***	-0.00273	-0.00687
	(0.00929)	(0.0146)	(0.0181)	(0.00264)	(0.00522)
% of land=Savannas	-0.00197	-0.00352	-0.00407	-0.000363	-0.00136
	(0.00148)	(0.00223)	(0.00381)	(0.000403)	(0.000935)
% of land=Grasslands	0.000385	0.000288	-0.00116	-0.000661	-0.00170
	(0.00173)	(0.00224)	(0.00424)	(0.000563)	(0.00129)
% of land=Broadleaf forest	0.000563	-0.00435	-0.00482	-0.000345	-0.00198
	(0.00286)	(0.00496)	(0.00740)	(0.000812)	(0.00186)
% of land=Urban	-0.00121	-0.00595*	-0.0172**	-0.00110	-0.00282
	(0.00189)	(0.00335)	(0.00786)	(0.000722)	(0.00173)
prov=CD	0.481***	0.999***	1.978***	0.0333	0.137*
	(0.0836)	(0.0935)	(0.345)	(0.0307)	(0.0787)
prov=NI	-0.165	-0.193	-1.078***	-0.103***	-0.246***
	(0.104)	(0.134)	(0.337)	(0.0318)	(0.0767)
prov=NP	0.260***	0.424***	0.310	0.0308	0.0805
	(0.0818)	(0.122)	(0.285)	(0.0252)	(0.0640)
prov=ZA	0.894***	0.880***	0.814***	-0.130***	-0.219***
	(0.0777)	(0.135)	(0.306)	(0.0302)	(0.0709)
prov=MA	0.109**	-0.108	-0.246	-0.00891	-0.0191
	(0.0455)	(0.0687)	(0.179)	(0.0147)	(0.0376)
prov=SF	-0.0417	0.647***	1.415***	-0.0299	-0.00726

	(0.0843)	(0.0911)	(0.277)	(0.0310)	(0.0768)
prov=IN	0.648***	1.056***	1.469***	-0.0891***	-0.104
	(0.0754)	(0.0915)	(0.294)	(0.0317)	(0.0764)
prov=GZ	0.543***	0.418***	0.792**	-0.00546	0.0331
	(0.0989)	(0.136)	(0.311)	(0.0278)	(0.0680)
prov=MP	0.815***	0.460***	0.241	-0.122***	-0.220***
	(0.0813)	(0.155)	(0.314)	(0.0278)	(0.0673)
prov=MC	0.527***	0.745***	0.784***	-0.0166	-0.0166
	(0.0882)	(0.119)	(0.286)	(0.0302)	(0.0770)
month=February	-0.00165	-0.0658	-0.198	-0.00678	-0.0200
	(0.0546)	(0.0778)	(0.135)	(0.0175)	(0.0383)
month=August	-0.00138	-0.0294	-0.174	-0.00996	-0.0332
	(0.0451)	(0.0563)	(0.114)	(0.0123)	(0.0267)
month=September	0.171**	0.330**	0.467**	0.0507**	0.139***
	(0.0764)	(0.136)	(0.231)	(0.0207)	(0.0462)
month=October	0.191**	0.393***	0.356	0.0278	0.0829*
	(0.0820)	(0.129)	(0.239)	(0.0208)	(0.0454)
month=November	0.226***	0.385***	0.499***	0.0308**	0.0975***
	(0.0468)	(0.0605)	(0.147)	(0.0139)	(0.0309)
month=December	0.139*	0.147*	0.739***	0.0696***	0.173***
	(0.0716)	(0.0869)	(0.151)	(0.0160)	(0.0343)
Constant	4.128***	7.682***	5.610***	0.650***	2.346***
	(0.133)	(0.202)	(0.406)	(0.0486)	(0.118)
Observations	11,836	11,836	11,836	11,836	11,836
R-squared	0.348	0.144	0.261	0.189	0.216

Note: food consumption and caloric intake have been transformed using the inverse hyperbolic sine transformation. Household sampling weights applied. Regression estimated through a linear model. Clustered standard errors at the district level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Source: authors' elaboration from IOF 2019/2020.

Table A10: Heterogeneity analysis - Household level, female vs male-headed household

Variables	Per capita food consumption	Per capita Caloric Intake	HDDS	Simpson	Shannon
2nd Trimester	0.0331	0.104	0.326***	0.0470***	0.117***
	(0.0508)	(0.0684)	(0.103)	(0.0155)	(0.0319)
3rd Trimester	-0.258***	-0.378***	-0.362*	-0.0305**	-0.0930***
	(0.0524)	(0.0981)	(0.186)	(0.0137)	(0.0305)
2nd Trimester* Female HH head	0.0147	0.0699	0.0229	-0.00506	-0.0145
	(0.0497)	(0.0713)	(0.120)	(0.0122)	(0.0279)
3rd Trimester* Female HH head	0.0464	0.0400	0.0813	0.0181	0.0279
	(0.0461)	(0.0668)	(0.112)	(0.0126)	(0.0285)
HH size	-0.0704***	-0.0533***	0.0662***	-0.00254*	-0.00186
	(0.00497)	(0.00591)	(0.0122)	(0.00153)	(0.00350)
Female headed HH	-0.0971***	-0.0476	-0.215**	-0.00952	-0.0228
	(0.0366)	(0.0531)	(0.0917)	(0.0108)	(0.0250)
Asset index	0.0771***	0.0224**	0.0830***	0.00666***	0.0169***
	(0.00589)	(0.00865)	(0.0196)	(0.00223)	(0.00533)
Dep. Ratio	-0.0541***	-0.0583***	-0.0665***	-0.00975***	-0.0223***
	(0.00958)	(0.0149)	(0.0247)	(0.00306)	(0.00625)
HH with children	-0.213***	-0.119***	0.311***	0.0113	0.0483**
	(0.0273)	(0.0449)	(0.0716)	(0.00861)	(0.0191)
% employed	0.245***	0.138***	0.216**	-0.00651	-0.00584
	(0.0495)	(0.0525)	(0.0993)	(0.0103)	(0.0242)
HH head has primary+ educ.	0.0197	-0.0522*	0.147***	0.0209***	0.0461***
	(0.0172)	(0.0265)	(0.0455)	(0.00633)	(0.0132)
HH owns land	-0.00819	0.0682	-0.0833	0.00951	0.0109
	(0.0305)	(0.0419)	(0.0890)	(0.00924)	(0.0218)
TLUs	-0.000804	0.000803**	0.000789	-7.27e-05	-0.000251*
	(0.000691)	(0.000389)	(0.000574)	(6.95e-05)	(0.000152)
HH is subsistence ag.	-0.0143	0.0793	-0.671***	-0.0876***	-0.206***
	(0.0474)	(0.0994)	(0.143)	(0.0121)	(0.0307)
Rural	-0.0173	-0.141*	-0.564***	-0.0193	-0.0577**
	(0.0409)	(0.0726)	(0.105)	(0.0124)	(0.0262)
HH receives social assistence	-0.125***	-0.0975	-0.0496	0.00475	0.0122
	(0.0411)	(0.0646)	(0.103)	(0.0143)	(0.0276)
Access to city (in hours)	0.0151	-0.00116	-0.0612***	-0.00270	-0.00682
	(0.00929)	(0.0146)	(0.0181)	(0.00264)	(0.00523)
% of land=Savannas	-0.00195	-0.00347	-0.00405	-0.000362	-0.00136
	(0.00148)	(0.00223)	(0.00381)	(0.000400)	(0.000932)
% of land=Grasslands	0.000408	0.000354	-0.00113	-0.000658	-0.00170
	(0.00172)	(0.00224)	(0.00424)	(0.000560)	(0.00128)
% of land=Broadleaf forest	0.000612	-0.00421	-0.00478	-0.000339	-0.00196
	(0.00284)	(0.00495)	(0.00738)	(0.000806)	(0.00185)
% of land=Urban	-0.00121	-0.00594*	-0.0172**	-0.00110	-0.00282
	(0.00187)	(0.00334)	(0.00785)	(0.000719)	(0.00172)
prov=CD	0.480***	0.999***	1.976***	0.0330	0.136*
	(0.0829)	(0.0926)	(0.344)	(0.0307)	(0.0788)
prov=NI	-0.167	-0.194	-1.080***	-0.104***	-0.247***
	(0.103)	(0.133)	(0.336)	(0.0318)	(0.0767)
prov=NP	0.258***	0.421***	0.308	0.0303	0.0795
	(0.0816)	(0.121)	(0.284)	(0.0252)	(0.0640)
prov=ZA	0.894***	0.880***	0.814***	-0.130***	-0.218***
	(0.0774)	(0.134)	(0.305)	(0.0302)	(0.0709)
prov=MA	0.109**	-0.108	-0.248	-0.00922	-0.0194
	(0.0455)	(0.0684)	(0.179)	(0.0146)	(0.0374)
prov=SF	-0.0422	0.647***	1.413***	-0.0301	-0.00732

	(0.0842)	(0.0911)	(0.276)	(0.0310)	(0.0769)
prov=IN	0.648***	1.055***	1.468***	-0.0893***	-0.105
	(0.0750)	(0.0906)	(0.294)	(0.0317)	(0.0764)
prov=GZ	0.544***	0.419***	0.793**	-0.00515	0.0340
	(0.0982)	(0.135)	(0.310)	(0.0278)	(0.0680)
prov=MP	0.815***	0.460***	0.239	-0.122***	-0.220***
	(0.0812)	(0.155)	(0.313)	(0.0278)	(0.0673)
prov=MC	0.527***	0.745***	0.783***	-0.0167	-0.0163
	(0.0875)	(0.117)	(0.285)	(0.0302)	(0.0771)
month=February	-0.00199	-0.0666	-0.198	-0.00683	-0.0201
	(0.0545)	(0.0774)	(0.135)	(0.0175)	(0.0384)
month=August	-0.00143	-0.0292	-0.174	-0.0100	-0.0333
	(0.0452)	(0.0564)	(0.114)	(0.0123)	(0.0268)
month=September	0.172**	0.324**	0.468**	0.0522**	0.142***
	(0.0771)	(0.138)	(0.232)	(0.0203)	(0.0456)
month=October	0.190**	0.386***	0.355	0.0289	0.0857*
	(0.0802)	(0.125)	(0.235)	(0.0205)	(0.0449)
month=November	0.224***	0.377***	0.496***	0.0311**	0.0987***
	(0.0461)	(0.0610)	(0.146)	(0.0137)	(0.0304)
month=December	0.139*	0.146*	0.738***	0.0695***	0.173***
	(0.0715)	(0.0867)	(0.150)	(0.0160)	(0.0344)
Constant	4.138***	7.713***	5.629***	0.651***	2.343***
	(0.133)	(0.191)	(0.390)	(0.0471)	(0.113)
Observations	11,836	11,836	11,836	11,836	11,836
R-squared	0.348	0.144	0.261	0.189	0.216

Note: food consumption and caloric intake have been transformed using the inverse hyperbolic sine transformation. Household sampling weights applied. Regression estimated through a linear model. Clustered standard errors at the district level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Source: authors' elaboration from IOF 2019/2020.

Table A11: Heterogeneity analysis - Household level, subsistence ag. HHs vs other HHs

Variables	**Per capita food consumption**	**Per capita Caloric Intake**	**HDDS**	**Simpson**	**Shannon**
2nd Trimester	-0.00566	0.000776	0.271**	0.0364**	0.105***
	(0.0550)	(0.0648)	(0.128)	(0.0164)	(0.0361)
3rd Trimester	-0.258***	-0.372***	-0.443**	-0.0331**	-0.107***
	(0.0541)	(0.104)	(0.213)	(0.0139)	(0.0327)
2nd Trimester* Subsistence ag. HH	0.0704	0.197**	0.110	0.0156	0.0145
	(0.0530)	(0.0799)	(0.133)	(0.0174)	(0.0383)
3rd Trimester* Subsistence ag. HH	0.0876	0.125	0.416***	0.0372**	0.0869**
	(0.0576)	(0.0869)	(0.142)	(0.0169)	(0.0394)
HH size	-0.0703***	-0.0532***	0.0667***	-0.00250	-0.00176
	(0.00496)	(0.00582)	(0.0121)	(0.00152)	(0.00347)
Female headed HH	-0.0728***	-0.00648	-0.171***	-0.00378	-0.0160
	(0.0187)	(0.0279)	(0.0466)	(0.00633)	(0.0142)
Asset index	0.0770***	0.0221**	0.0828***	0.00666***	0.0169***
	(0.00591)	(0.00864)	(0.0197)	(0.00224)	(0.00535)
Dep. Ratio	-0.0543***	-0.0583***	-0.0673***	-0.00985***	-0.0225***
	(0.00959)	(0.0151)	(0.0246)	(0.00307)	(0.00624)
HH with children	-0.213***	-0.120***	0.309***	0.0111	0.0477**
	(0.0273)	(0.0451)	(0.0711)	(0.00852)	(0.0189)
% employed	0.244***	0.137**	0.211**	-0.00687	-0.00670
	(0.0495)	(0.0528)	(0.0983)	(0.0102)	(0.0240)
HH head has primary+ educ.	0.0210	-0.0488*	0.149***	0.0212***	0.0464***
	(0.0173)	(0.0267)	(0.0454)	(0.00629)	(0.0131)
HH owns land	-0.00844	0.0653	-0.0778	0.00979	0.0122
	(0.0306)	(0.0416)	(0.0894)	(0.00922)	(0.0217)
TLUs	-0.000830	0.000753*	0.000696	-8.26e-05	-0.000271*
	(0.000691)	(0.000395)	(0.000591)	(7.00e-05)	(0.000153)
HH is subsistence ag.	-0.0724	-0.0378	-0.866***	-0.107***	-0.244***
	(0.0603)	(0.104)	(0.171)	(0.0162)	(0.0400)
Rural	-0.0177	-0.141*	-0.572***	-0.0196	-0.0590**
	(0.0410)	(0.0724)	(0.105)	(0.0123)	(0.0260)
HH receives social assistence	-0.126***	-0.0960	-0.0567	0.00395	0.0101
	(0.0416)	(0.0648)	(0.103)	(0.0146)	(0.0283)
Access to city (in hours)	0.0153	-0.000928	-0.0605***	-0.00264	-0.00667
	(0.00942)	(0.0148)	(0.0183)	(0.00262)	(0.00522)
% of land=Savannas	-0.00187	-0.00344	-0.00348	-0.000314	-0.00123
	(0.00148)	(0.00218)	(0.00374)	(0.000399)	(0.000918)
% of land=Grasslands	0.000494	0.000430	-0.000622	-0.000614	-0.00158
	(0.00172)	(0.00221)	(0.00421)	(0.000564)	(0.00129)
% of land=Broadleaf forest	0.000755	-0.00414	-0.00384	-0.000258	-0.00175
	(0.00284)	(0.00487)	(0.00729)	(0.000808)	(0.00183)
% of land=Urban	-0.00112	-0.00607*	-0.0162**	-0.00103	-0.00259
	(0.00191)	(0.00335)	(0.00799)	(0.000730)	(0.00175)
prov=CD	0.478***	0.995***	1.961***	0.0320	0.133*
	(0.0839)	(0.0929)	(0.349)	(0.0310)	(0.0794)
prov=NI	-0.167	-0.198	-1.084***	-0.104***	-0.247***
	(0.104)	(0.133)	(0.341)	(0.0319)	(0.0773)
prov=NP	0.255***	0.414***	0.302	0.0298	0.0788
	(0.0824)	(0.122)	(0.289)	(0.0254)	(0.0646)
prov=ZA	0.892***	0.873***	0.813***	-0.130***	-0.218***
	(0.0788)	(0.134)	(0.309)	(0.0304)	(0.0716)
prov=MA	0.108**	-0.110	-0.251	-0.00927	-0.0197
	(0.0458)	(0.0688)	(0.182)	(0.0147)	(0.0377)
prov=SF	-0.0424	0.646***	1.408***	-0.0302	-0.00797

	(0.0850)	(0.0908)	(0.280)	(0.0312)	(0.0775)
prov=IN	0.646***	1.049***	1.469***	-0.0892***	-0.104
	(0.0758)	(0.0915)	(0.298)	(0.0321)	(0.0774)
prov=GZ	0.538***	0.412***	0.765**	-0.00763	0.0281
	(0.0992)	(0.136)	(0.313)	(0.0279)	(0.0683)
prov=MP	0.814***	0.459***	0.230	-0.123***	-0.222***
	(0.0818)	(0.154)	(0.316)	(0.0277)	(0.0673)
prov=MC	0.524***	0.739***	0.775***	-0.0173	-0.0175
	(0.0884)	(0.117)	(0.287)	(0.0302)	(0.0771)
month=February	0.00181	-0.0593	-0.185	-0.00552	-0.0175
	(0.0544)	(0.0776)	(0.133)	(0.0172)	(0.0381)
month=August	-0.00108	-0.0268	-0.177	-0.0101	-0.0341
	(0.0449)	(0.0559)	(0.113)	(0.0122)	(0.0263)
month=September	0.130*	0.253*	0.310	0.0364*	0.109**
	(0.0765)	(0.133)	(0.227)	(0.0205)	(0.0465)
month=October	0.149*	0.315**	0.197	0.0133	0.0528
	(0.0811)	(0.126)	(0.232)	(0.0210)	(0.0462)
month=November	0.187***	0.308***	0.360**	0.0178	0.0714**
	(0.0479)	(0.0581)	(0.142)	(0.0149)	(0.0341)
month=December	0.135*	0.138	0.725***	0.0682***	0.170***
	(0.0727)	(0.0889)	(0.155)	(0.0158)	(0.0339)
Constant	4.161***	7.773***	5.690***	0.657***	2.353***
	(0.136)	(0.196)	(0.397)	(0.0466)	(0.113)
Observations	11,836	11,836	11,836	11,836	11,836
R-squared	0.348	0.145	0.263	0.190	0.217

Note: food consumption and caloric intake have been transformed using the inverse hyperbolic sine transformation. Household sampling weights applied. Regression estimated through a linear model. Clustered standard errors at the district level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Source: authors' elaboration from IOF 2019/2020.

Table A12: Heterogeneity analysis - Household level, prevalence of stunting at district level

Variables	Per capita food consumption	Per capita Caloric Intake	HDDS	Simpson	Shannon
midrule					
2nd Trimester	-0.0207	0.142	0.147	0.0128	0.0505
	(0.0659)	(0.0929)	(0.163)	(0.0216)	(0.0444)
3rd Trimester	-0.251***	-0.378***	-0.402*	-0.0234	-0.0809**
	(0.0580)	(0.107)	(0.214)	(0.0154)	(0.0338)
2nd Trimester* Stunting (district average)	0.230	-0.0374	0.656	0.115**	0.215*
	(0.176)	(0.265)	(0.426)	(0.0561)	(0.115)
3rd Trimester* Stunting (district average)	0.0857	0.00252	0.597	0.0262	0.0644
	(0.204)	(0.270)	(0.384)	(0.0570)	(0.110)
Stunting (district average)	-0.159	0.0158	-0.877**	-0.0728	-0.176*
	(0.147)	(0.285)	(0.354)	(0.0538)	(0.105)
HH size	-0.0685***	-0.0524***	0.0718***	-0.00132	0.000928
	(0.00505)	(0.00593)	(0.0125)	(0.00155)	(0.00355)
Female headed HH	-0.0650***	0.0173	-0.148***	-0.00436	-0.0126
	(0.0189)	(0.0258)	(0.0481)	(0.00664)	(0.0147)
Asset index	0.0764***	0.0204**	0.0762***	0.00621***	0.0152***
	(0.00607)	(0.00868)	(0.0196)	(0.00225)	(0.00531)
Dep. Ratio	-0.0563***	-0.0665***	-0.0798***	-0.00879***	-0.0224***
	(0.0101)	(0.0157)	(0.0255)	(0.00320)	(0.00649)
HH with children	-0.219***	-0.135***	0.314***	0.00981	0.0411**
	(0.0258)	(0.0377)	(0.0709)	(0.00884)	(0.0197)
% employed	0.256***	0.142***	0.220**	-0.00543	-0.00333
	(0.0518)	(0.0539)	(0.103)	(0.0105)	(0.0247)
HH head has primary+ educ.	0.0176	-0.0507*	0.135***	0.0188***	0.0410***
	(0.0176)	(0.0278)	(0.0473)	(0.00649)	(0.0135)
HH owns land	0.0100	0.0938**	-0.0451	0.00687	0.0113
	(0.0307)	(0.0401)	(0.0939)	(0.00941)	(0.0226)
TLUs	-0.000828	0.00103**	0.00108*	-4.13e-05	-0.000151
	(0.000692)	(0.000501)	(0.000586)	(6.35e-05)	(0.000140)
HH is subsistence ag.	-0.0295	0.0220	-0.693***	-0.0788***	-0.200***
	(0.0468)	(0.0876)	(0.146)	(0.0121)	(0.0306)
Rural	-0.0166	-0.120	-0.559***	-0.0237*	-0.0638**
	(0.0431)	(0.0740)	(0.110)	(0.0125)	(0.0261)
HH receives social assistence	-0.111**	-0.0747	-0.00231	0.0161	0.0345
	(0.0463)	(0.0675)	(0.104)	(0.0166)	(0.0319)
Access to city (in hours)	0.0150	-0.00401	-0.0724***	-0.00310	-0.00920
	(0.0106)	(0.0167)	(0.0192)	(0.00299)	(0.00559)
% of land=Savannas	-0.00239	-0.00293	-0.00271	-0.000466	-0.00122
	(0.00156)	(0.00212)	(0.00456)	(0.000421)	(0.00105)
% of land=Grasslands	6.85e-05	0.00109	0.000154	-0.000796	-0.00165
	(0.00177)	(0.00207)	(0.00495)	(0.000602)	(0.00142)
% of land=Broadleaf forest	0.000331	-0.00249	-0.00161	-0.000346	-0.000898
	(0.00306)	(0.00421)	(0.00858)	(0.000919)	(0.00219)
% of land=Urban	-0.00156	-0.00536	-0.0168*	-0.00119	-0.00267
	(0.00196)	(0.00341)	(0.00850)	(0.000759)	(0.00183)
prov=CD	0.671***	1.202***	3.147***	0.134***	0.380***
	(0.107)	(0.148)	(0.259)	(0.0321)	(0.0741)
prov=NP	0.472***	0.682***	1.482***	0.137***	0.334***
	(0.101)	(0.155)	(0.224)	(0.0255)	(0.0575)
prov=ZA	1.077***	1.078***	1.977***	-0.0302	0.0211
	(0.109)	(0.179)	(0.268)	(0.0309)	(0.0648)
prov=TT	0.174	0.209	1.153***	0.0994***	0.242***
	(0.106)	(0.137)	(0.348)	(0.0330)	(0.0792)
prov=MA	0.284***	0.0902	0.864***	0.0917***	0.220***

	(0.0933)	(0.123)	(0.254)	(0.0295)	(0.0667)
prov=SF	0.143	0.839***	2.613***	0.0728**	0.246***
	(0.115)	(0.159)	(0.226)	(0.0341)	(0.0755)
prov=IN	0.857***	1.293***	2.659***	-0.000783	0.121*
	(0.106)	(0.146)	(0.264)	(0.0331)	(0.0726)
prov=GZ	0.725***	0.612***	1.885***	0.0912***	0.263***
	(0.116)	(0.162)	(0.258)	(0.0278)	(0.0610)
prov=MP	0.982***	0.648***	1.364***	-0.0254	0.0112
	(0.110)	(0.202)	(0.267)	(0.0302)	(0.0630)
prov=MC	0.714***	0.958***	1.968***	0.0854***	0.236***
	(0.123)	(0.174)	(0.259)	(0.0323)	(0.0728)
month=February	0.00259	-0.0676	-0.175	-0.00571	-0.0175
	(0.0549)	(0.0774)	(0.133)	(0.0172)	(0.0378)
month=August	-0.0164	-0.0499	-0.188	-0.0132	-0.0407
	(0.0473)	(0.0602)	(0.117)	(0.0127)	(0.0276)
month=September	0.155*	0.324**	0.339	0.0412*	0.116**
	(0.0912)	(0.161)	(0.240)	(0.0214)	(0.0477)
month=October	0.193**	0.433***	0.296	0.0237	0.0790*
	(0.0873)	(0.140)	(0.241)	(0.0219)	(0.0471)
month=November	0.216***	0.373***	0.429***	0.0242	0.0836**
	(0.0516)	(0.0721)	(0.146)	(0.0155)	(0.0336)
month=December	0.143**	0.143	0.743***	0.0711***	0.175***
	(0.0720)	(0.0874)	(0.151)	(0.0158)	(0.0339)
Constant	4.011***	7.448***	4.572***	0.574***	2.130***
	(0.169)	(0.229)	(0.507)	(0.0523)	(0.127)
Observations	11,216	11,216	11,216	11,216	11,216
R-squared	0.343	0.156	0.261	0.192	0.219

Note: food consumption and caloric intake have been transformed using the inverse hyperbolic sine transformation. Household sampling weights applied. Regression estimated through a linear model. Clustered standard errors at the district level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Source: authors' elaboration from IOF 2019/2020.

Table A13: Heterogeneity analysis - Household level, poor HHs vs. rich HHs

Variables	Per capita food consumption	Per capita Caloric Intake	HDDS	Simpson	Shannon
2nd Trimester	-0.0340	0.0649	0.205*	0.0306**	0.0892***
	(0.0521)	(0.0689)	(0.119)	(0.0131)	(0.0283)
3rd Trimester	-0.114**	-0.314***	-0.283	-0.0197	-0.0708**
	(0.0461)	(0.0902)	(0.185)	(0.0132)	(0.0301)
2nd Trimester*HH is poor	0.110**	0.108	0.107	0.0130	0.00833
	(0.0482)	(0.0718)	(0.130)	(0.0176)	(0.0371)
3rd Trimester*HH is poor	0.104*	-0.0190	0.285**	0.0167	0.0249
	(0.0553)	(0.0834)	(0.128)	(0.0162)	(0.0359)
HH is poor	-0.309***	-0.124**	-0.918***	-0.0872***	-0.212***
	(0.0453)	(0.0587)	(0.116)	(0.0145)	(0.0327)
HH size	-0.0652***	-0.0528***	0.0652***	-0.00274*	-0.00260
	(0.00497)	(0.00577)	(0.0120)	(0.00147)	(0.00339)
Female headed HH	-0.0629***	-0.00487	-0.169***	-0.00389	-0.0164
	(0.0194)	(0.0288)	(0.0478)	(0.00669)	(0.0149)
Dep. Ratio	-0.0709***	-0.0598***	-0.0828***	-0.0115***	-0.0261***
	(0.00928)	(0.0148)	(0.0238)	(0.00298)	(0.00617)
HH with children	-0.208***	-0.116**	0.326***	0.0127	0.0524***
	(0.0278)	(0.0454)	(0.0758)	(0.00885)	(0.0197)
% employed	0.209***	0.148***	0.184*	-0.0115	-0.0148
	(0.0491)	(0.0535)	(0.111)	(0.0117)	(0.0281)
HH head has primary+ educ.	0.0706***	-0.0484**	0.200***	0.0268***	0.0583***
	(0.0186)	(0.0242)	(0.0461)	(0.00651)	(0.0138)
HH owns land	-0.0813**	0.0747*	-0.270***	-0.0142	-0.0426*
	(0.0347)	(0.0388)	(0.0907)	(0.00927)	(0.0228)
TLUs	0.000188	0.00103***	0.00145**	-2.24e-05	-0.000131
	(0.000920)	(0.000383)	(0.000590)	(7.83e-05)	(0.000177)
Rural	-0.0820**	-0.125**	-0.679***	-0.0337***	-0.0879***
	(0.0392)	(0.0622)	(0.108)	(0.0114)	(0.0246)
HH receives social assistence	-0.141***	-0.0971	-0.0907	-2.41e-05	0.000478
	(0.0419)	(0.0651)	(0.102)	(0.0152)	(0.0294)
Access to city (in hours)	0.0128	-0.000920	-0.0567***	-0.00218	-0.00541
	(0.00872)	(0.0146)	(0.0181)	(0.00265)	(0.00519)
% of land=Savannas	-0.00237*	-0.00356	-0.00430	-0.000416	-0.00145
	(0.00136)	(0.00222)	(0.00369)	(0.000408)	(0.000935)
% of land=Grasslands	0.000246	0.000317	-0.000671	-0.000625	-0.00159
	(0.00162)	(0.00229)	(0.00408)	(0.000582)	(0.00132)
% of land=Broadleaf forest	-0.000239	-0.00412	-0.00548	-0.000487	-0.00222
	(0.00270)	(0.00487)	(0.00711)	(0.000830)	(0.00183)
% of land=Urban	0.000482	-0.00547	-0.0130	-0.000741	-0.00183
	(0.00208)	(0.00337)	(0.00855)	(0.000753)	(0.00182)
prov=CD	0.301***	0.969***	1.815***	0.0193	0.105
	(0.103)	(0.0923)	(0.371)	(0.0314)	(0.0808)
prov=NI	-0.290**	-0.235*	-1.348***	-0.129***	-0.312***
	(0.114)	(0.131)	(0.334)	(0.0301)	(0.0721)
prov=NP	0.112	0.387***	0.0108	0.00134	0.00720
	(0.0956)	(0.120)	(0.297)	(0.0242)	(0.0616)
prov=ZA	0.731***	0.839***	0.658**	-0.143***	-0.249***
	(0.0965)	(0.131)	(0.331)	(0.0291)	(0.0693)
prov=MA	0.0587	-0.128*	-0.335*	-0.0165	-0.0390
	(0.0678)	(0.0674)	(0.178)	(0.0138)	(0.0347)
prov=SF	-0.238**	0.612***	1.259***	-0.0430	-0.0358
	(0.101)	(0.0891)	(0.300)	(0.0309)	(0.0767)
prov=IN	0.446***	1.021***	1.274***	-0.108***	-0.145*
	(0.0970)	(0.0881)	(0.322)	(0.0328)	(0.0786)
prov=GZ	0.377***	0.385***	0.674**	-0.0135	0.0153

	(0.106)	(0.132)	(0.325)	(0.0274)	(0.0672)
prov=MP	0.632***	0.417***	0.145	-0.127***	-0.231***
	(0.0966)	(0.152)	(0.334)	(0.0278)	(0.0668)
prov=MC	0.343***	0.704***	0.687**	-0.0223	-0.0280
	(0.104)	(0.118)	(0.310)	(0.0307)	(0.0781)
month=February	0.000385	-0.0640	-0.221	-0.00985	-0.0275
	(0.0546)	(0.0772)	(0.144)	(0.0189)	(0.0422)
month=August	-0.000648	-0.0360	-0.132	-0.00473	-0.0208
	(0.0458)	(0.0568)	(0.116)	(0.0126)	(0.0275)
month=September	-0.0271	0.282**	0.207	0.0324	0.103**
	(0.0759)	(0.137)	(0.215)	(0.0202)	(0.0454)
month=October	-0.000887	0.343***	0.0993	0.00976	0.0470
	(0.0780)	(0.124)	(0.214)	(0.0206)	(0.0448)
month=November	0.0305	0.327***	0.241*	0.0104	0.0560*
	(0.0484)	(0.0587)	(0.141)	(0.0147)	(0.0336)
month=December	0.113	0.132	0.678***	0.0648***	0.162***
	(0.0695)	(0.0869)	(0.138)	(0.0172)	(0.0370)
Constant	4.576***	7.830***	6.082***	0.688***	2.427***
	(0.140)	(0.204)	(0.416)	(0.0446)	(0.108)
Observations	11,836	11,836	11,836	11,836	11,836
R-squared	0.321	0.143	0.254	0.174	0.203

Note: food consumption and caloric intake have been transformed using the inverse hyperbolic sine transformation. Household is defined poor if in the first or second lowest quintile of the wealth distribution. Household sampling weights applied. Regression estimated through a linear model. Clustered standard errors at the district level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Source: authors' elaboration from IOF 2019/2020.

Table A14: Heterogeneity analysis - Child level, newborn vs. other children

Variables	**Stunting**	**Wasting**	**Underweight**	**Overweight**
2nd Trimester	0.0610**	-0.0186*	-0.0647***	0.0267*
	(0.0298)	(0.0111)	(0.0205)	(0.0140)
3rd Trimester	0.0579*	6.83e-05	-0.0227	0.0105
	(0.0347)	(0.0145)	(0.0217)	(0.0154)
2nd Trimester* Newborn	0.127***	-0.000518	0.0389	-0.0140
	(0.0387)	(0.0126)	(0.0308)	(0.0182)
3rd Trimester* Newborn	0.206***	-0.0196	0.0618**	0.0191
	(0.0341)	(0.0136)	(0.0276)	(0.0199)
HH size	0.00800***	0.000305	0.00135	-0.000491
	(0.00278)	(0.00150)	(0.00201)	(0.00100)
Female headed HH	0.0193	0.0117	0.0123	-0.0261***
	(0.0215)	(0.00724)	(0.0159)	(0.00964)
Asset index	-0.0383***	-0.00118	-0.0209***	0.000982
	(0.00590)	(0.00270)	(0.00519)	(0.00208)
Dep. Ratio	0.0151	0.00150	0.0151***	-0.00222
	(0.00974)	(0.00358)	(0.00565)	(0.00392)
% employed	0.0315	-0.00125	0.0125	-0.0178
	(0.0337)	(0.0134)	(0.0236)	(0.0117)
HH head has primary+ educ.	-0.0195	-0.00695	-0.0137	-0.0141*
	(0.0140)	(0.00625)	(0.0124)	(0.00826)
HH owns land	0.0364	0.000481	0.0137	-0.0149
	(0.0391)	(0.0148)	(0.0343)	(0.0183)
TLUs	-0.00209	-0.00135	-5.60e-05	1.75e-05
	(0.00271)	(0.00150)	(0.000449)	(8.55e-05)
HH is subsistence ag.	-0.00117	0.00996	-0.000606	0.0103
	(0.0228)	(0.00972)	(0.0153)	(0.00948)
Rural	-0.00330	-0.00148	-0.00437	0.0200*
	(0.0214)	(0.00887)	(0.0207)	(0.0109)
HH receives social assistence	0.00185	0.0301*	-0.00185	-0.0327
	(0.0307)	(0.0171)	(0.0415)	(0.0226)
Female	-0.0612***	0.000680	-0.0310**	-0.00704
	(0.0138)	(0.00527)	(0.0131)	(0.00673)
Newborn	-0.364***	0.0504***	-0.0571**	-0.00693
	(0.0262)	(0.0104)	(0.0231)	(0.0169)
Firstborn	0.0232	-0.00446	0.0243	0.00268
	(0.0212)	(0.0107)	(0.0170)	(0.0107)
Access to city (in hours)	-0.0102**	-0.00114	-0.00468	0.00111
	(0.00487)	(0.00167)	(0.00354)	(0.00175)
% of land=Savannas	0.000365	2.60e-05	0.000368	0.000148
	(0.000614)	(0.000243)	(0.000619)	(0.000345)
% of land=Grasslands	0.000692	5.97e-05	0.000987	-0.000189
	(0.000746)	(0.000244)	(0.000698)	(0.000412)
% of land=Broadleaf forest	0.00170	7.02e-05	0.00105	0.000199
	(0.00130)	(0.000453)	(0.00102)	(0.000459)
% of land=Urban	3.93e-05	0.000113	-0.00132	0.000180
	(0.00144)	(0.00107)	(0.00178)	(0.000541)
prov=CD	0.100**	-0.0187	-0.0260	-0.00414
	(0.0459)	(0.0359)	(0.0668)	(0.0205)
prov=NI	0.0999**	0.0351	0.0296	0.0209
	(0.0470)	(0.0366)	(0.0703)	(0.0223)
prov=NP	0.0540	0.00661	-0.0351	0.0293
	(0.0472)	(0.0373)	(0.0702)	(0.0208)
prov=ZA	0.0485	-0.00868	-0.00155	-0.0181
	(0.0457)	(0.0359)	(0.0693)	(0.0226)
prov=TT	-0.000246	-0.00458	-0.0576	0.00851
	(0.0524)	(0.0381)	(0.0699)	(0.0229)
prov=MA	0.0378	-0.0219	-0.0515	-0.00217
	(0.0498)	(0.0373)	(0.0688)	(0.0208)

prov=SF	-0.0199	-0.00544	-0.0544	0.00391
	(0.0508)	(0.0355)	(0.0682)	(0.0214)
prov=IN	-0.120**	-0.0176	-0.125*	0.0194
	(0.0493)	(0.0381)	(0.0679)	(0.0206)
prov=GZ	-0.0692	-0.00572	-0.101	0.0340
	(0.0566)	(0.0369)	(0.0715)	(0.0235)
prov=MP	-0.221***	-0.0150	-0.0886	0.0153
	(0.0367)	(0.0345)	(0.0572)	(0.0169)
month=February	0.0398	0.00888	0.0250	-0.0180
	(0.0311)	(0.0108)	(0.0214)	(0.0162)
month=July	0.0339	-0.00583	0.0375*	0.0119
	(0.0269)	(0.0118)	(0.0216)	(0.0114)
month=September	0.000820	0.00178	0.00492	0.00970
	(0.0314)	(0.0117)	(0.0248)	(0.0164)
month=October	-0.0320	0.00840	-0.0167	-0.00617
	(0.0322)	(0.0130)	(0.0209)	(0.0150)
month=December	0.0270	-0.0124	-0.0690**	-0.00492
	(0.0373)	(0.0161)	(0.0337)	(0.0204)
Observations	6,581	6,566	6,578	6,566

Note: household sampling weights applied. Regression estimated through a probability model. Estimated coefficients represent average marginal effects. Clustered standard errors at the district level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Source: authors' elaboration from IOF 2019/2020.

Table A15: Heterogeneity analysis - Child level, female vs. male

Variables	Stunting	Wasting	Underweight	Overweight
2nd Trimester	0.0639**	-0.00107	-0.0469**	0.0192
	(0.0323)	(0.0127)	(0.0228)	(0.0157)
3rd Trimester	0.116***	-0.0141	0.00553	0.0190
	(0.0362)	(0.0142)	(0.0236)	(0.0185)
2nd Trimester* Female	0.0363	-0.0380**	-0.0206	0.00705
	(0.0264)	(0.0149)	(0.0255)	(0.0135)
3rd Trimester* Female	-0.0230	0.00860	-0.0239	-0.00186
	(0.0304)	(0.0128)	(0.0266)	(0.0168)
HH size	0.00793***	0.000327	0.00124	-0.000495
	(0.00283)	(0.00149)	(0.00204)	(0.00101)
Female headed HH	0.0206	0.0121*	0.0124	-0.0258***
	(0.0213)	(0.00715)	(0.0160)	(0.00967)
Asset index	-0.0387***	-0.00101	-0.0209***	0.000844
	(0.00586)	(0.00265)	(0.00521)	(0.00207)
Dep. Ratio	0.0155	0.00103	0.0156***	-0.00230
	(0.00967)	(0.00355)	(0.00578)	(0.00393)
% employed	0.0342	-0.00195	0.0133	-0.0178
	(0.0336)	(0.0134)	(0.0237)	(0.0118)
HH head has primary+ educ.	-0.0189	-0.00668	-0.0135	-0.0142*
	(0.0139)	(0.00629)	(0.0125)	(0.00830)
HH owns land	0.0378	-0.00118	0.0144	-0.0144
	(0.0393)	(0.0149)	(0.0347)	(0.0182)
TLUs	-0.00172	-0.00150	-3.04e-05	2.23e-05
	(0.00275)	(0.00149)	(0.000383)	(8.39e-05)
HH is subsistence ag.	-0.000333	0.0104	-3.18e-05	0.0100
	(0.0228)	(0.00962)	(0.0153)	(0.00946)
Rural	-0.00432	-0.000910	-0.00433	0.0198*
	(0.0213)	(0.00891)	(0.0209)	(0.0109)
HH receives social assistence	-0.00245	0.0303*	-0.00289	-0.0334
	(0.0305)	(0.0167)	(0.0421)	(0.0225)
Female	-0.0642***	0.00712	-0.0149	-0.00912
	(0.0193)	(0.0101)	(0.0170)	(0.0135)
Newborn	-0.228***	0.0417***	-0.0173*	-0.00379
	(0.0143)	(0.00528)	(0.0104)	(0.00764)
Firstborn	0.0225	-0.00491	0.0239	0.00261
	(0.0210)	(0.0107)	(0.0169)	(0.0108)
Access to city (in hours)	-0.0103**	-0.00121	-0.00475	0.00109
	(0.00486)	(0.00163)	(0.00357)	(0.00176)
% of land=Savannas	0.000372	5.10e-05	0.000394	0.000168
	(0.000637)	(0.000235)	(0.000623)	(0.000347)
% of land=Grasslands	0.000709	6.79e-05	0.00103	-0.000173
	(0.000769)	(0.000236)	(0.000703)	(0.000414)
% of land=Broadleaf forest	0.00171	0.000123	0.00107	0.000208
	(0.00132)	(0.000442)	(0.00102)	(0.000458)
% of land=Urban	0.000297	9.61e-05	-0.00121	0.000227
	(0.00145)	(0.00109)	(0.00179)	(0.000540)
prov=CD	0.0976**	-0.0184	-0.0269	-0.00541
	(0.0471)	(0.0371)	(0.0673)	(0.0204)
prov=NI	0.101**	0.0352	0.0300	0.0203
	(0.0480)	(0.0375)	(0.0709)	(0.0222)
prov=NP	0.0569	0.00553	-0.0345	0.0288
	(0.0478)	(0.0382)	(0.0708)	(0.0207)
prov=ZA	0.0506	-0.00975	-0.000318	-0.0179
	(0.0464)	(0.0370)	(0.0699)	(0.0225)
prov=TT	-5.24e-05	-0.00327	-0.0576	0.00784
	(0.0538)	(0.0389)	(0.0704)	(0.0227)
prov=MA	0.0386	-0.0219	-0.0511	-0.00264
	(0.0507)	(0.0381)	(0.0693)	(0.0207)

prov=SF	-0.0173	-0.00581	-0.0534	0.00335
	(0.0521)	(0.0364)	(0.0689)	(0.0213)
prov=IN	-0.119**	-0.0176	-0.124*	0.0186
	(0.0504)	(0.0388)	(0.0684)	(0.0205)
prov=GZ	-0.0649	-0.00555	-0.0990	0.0340
	(0.0583)	(0.0377)	(0.0720)	(0.0233)
prov=MP	-0.221***	-0.0169	-0.0886	0.0150
	(0.0380)	(0.0346)	(0.0579)	(0.0169)
month=February	0.0389	0.00872	0.0250	-0.0180
	(0.0305)	(0.0107)	(0.0214)	(0.0162)
month=July	0.0328	-0.00450	0.0377*	0.0113
	(0.0268)	(0.0118)	(0.0216)	(0.0115)
month=September	-0.000262	0.00215	0.00406	0.00859
	(0.0325)	(0.0117)	(0.0249)	(0.0166)
month=October	-0.0317	0.00845	-0.0167	-0.00688
	(0.0333)	(0.0129)	(0.0211)	(0.0151)
month=December	0.0296	-0.0124	-0.0682**	-0.00467
	(0.0364)	(0.0159)	(0.0339)	(0.0207)
Observations	6,581	6,566	6,578	6,566

Note: household sampling weights applied. Regression estimated through a probability model. Estimated coefficients represent average marginal effects. Clustered standard errors at the district level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Source: authors' elaboration from IOF 2019/2020.

Table A16: Heterogeneity analysis - Child level, firstborn vs. other children

Variables	Stunting	Wasting	underweight	overweight
2nd Trimester	0.0909***	-0.0218**	-0.0470**	0.0165
	(0.0295)	(0.0108)	(0.0213)	(0.0139)
3rd Trimester	0.0991***	-0.0129	0.00263	0.00740
	(0.0333)	(0.0129)	(0.0225)	(0.0157)
2nd Trimester* Firstborn	-0.0579	0.0318*	-0.0530*	0.0518**
	(0.0455)	(0.0183)	(0.0289)	(0.0223)
3rd Trimester* Firstborn	0.0312	0.0304	-0.0470	0.0782***
	(0.0483)	(0.0210)	(0.0302)	(0.0258)
HH size	0.00804***	0.000342	0.00134	-0.000470
	(0.00286)	(0.00153)	(0.00203)	(0.00101)
Female headed HH	0.0208	0.0115	0.0129	-0.0255***
	(0.0213)	(0.00731)	(0.0160)	(0.00960)
Asset index	-0.0385***	-0.00108	-0.0209***	0.000862
	(0.00590)	(0.00271)	(0.00520)	(0.00207)
Dep. Ratio	0.0154	0.00164	0.0154***	-0.00221
	(0.00957)	(0.00362)	(0.00572)	(0.00401)
% employed	0.0338	-0.00124	0.0130	-0.0179
	(0.0334)	(0.0132)	(0.0239)	(0.0120)
HH head has primary+ educ.	-0.0182	-0.00683	-0.0134	-0.0138*
	(0.0140)	(0.00633)	(0.0124)	(0.00821)
HH owns land	0.0376	-0.000992	0.0166	-0.0146
	(0.0397)	(0.0147)	(0.0350)	(0.0182)
TLUs	-0.00181	-0.00143	-4.81e-05	3.79e-05
	(0.00274)	(0.00153)	(0.000386)	(8.60e-05)
HH is subsistence ag.	0.000267	0.00964	0.000369	0.00981
	(0.0227)	(0.00993)	(0.0152)	(0.00945)
Rural	-0.00397	-0.00116	-0.00525	0.0204*
	(0.0213)	(0.00897)	(0.0204)	(0.0108)
HH receives social assistence	-0.00352	0.0308*	-0.00386	-0.0338
	(0.0306)	(0.0176)	(0.0407)	(0.0224)
Female	-0.0606***	0.000725	-0.0310**	-0.00665
	(0.0135)	(0.00524)	(0.0130)	(0.00685)
Newborn	-0.228***	0.0419***	-0.0177*	-0.00371
	(0.0144)	(0.00528)	(0.0104)	(0.00754)
Firstborn	0.0306	-0.0285*	0.0603***	-0.0546***
	(0.0305)	(0.0169)	(0.0230)	(0.0203)
Access to city (in hours)	-0.0104**	-0.00123	-0.00463	0.00102
	(0.00487)	(0.00167)	(0.00359)	(0.00175)
% of land=Savannas	0.000411	2.80e-05	0.000372	0.000185
	(0.000628)	(0.000242)	(0.000625)	(0.000347)
% of land=Grasslands	0.000713	6.50e-05	0.00100	-0.000171
	(0.000763)	(0.000241)	(0.000701)	(0.000413)
% of land=Broadleaf forest	0.00179	0.000117	0.00104	0.000254
	(0.00132)	(0.000454)	(0.00102)	(0.000458)
% of land=Urban	0.000299	4.56e-05	-0.00120	0.000207
	(0.00145)	(0.00108)	(0.00178)	(0.000546)
prov=CD	0.0980**	-0.0181	-0.0268	-0.00589
	(0.0465)	(0.0361)	(0.0666)	(0.0206)
prov=NI	0.102**	0.0354	0.0298	0.0201
	(0.0477)	(0.0368)	(0.0702)	(0.0224)
prov=NP	0.0572	0.00680	-0.0350	0.0291
	(0.0479)	(0.0373)	(0.0701)	(0.0210)
prov=ZA	0.0500	-0.00917	-0.000205	-0.0193
	(0.0461)	(0.0361)	(0.0692)	(0.0227)
prov=TT	0.00147	-0.00349	-0.0587	0.00817
	(0.0535)	(0.0383)	(0.0700)	(0.0229)
prov=MA	0.0387	-0.0224	-0.0505	-0.00353
	(0.0504)	(0.0373)	(0.0686)	(0.0210)

prov=SF	-0.0173	-0.00539	-0.0538	0.00306
	(0.0518)	(0.0356)	(0.0681)	(0.0216)
prov=IN	-0.118**	-0.0170	-0.125*	0.0182
	(0.0502)	(0.0382)	(0.0677)	(0.0209)
prov=GZ	-0.0630	-0.00585	-0.0989	0.0344
	(0.0577)	(0.0370)	(0.0715)	(0.0236)
prov=MP	-0.222***	-0.0143	-0.0895	0.0151
	(0.0374)	(0.0346)	(0.0574)	(0.0172)
month=February	0.0391	0.00793	0.0260	-0.0202
	(0.0304)	(0.0107)	(0.0213)	(0.0161)
month=July	0.0361	-0.00604	0.0381*	0.0117
	(0.0267)	(0.0115)	(0.0215)	(0.0115)
month=September	-0.000267	0.00200	0.00416	0.00839
	(0.0321)	(0.0119)	(0.0248)	(0.0164)
month=October	-0.0329	0.00832	-0.0165	-0.00782
	(0.0330)	(0.0131)	(0.0210)	(0.0148)
month=December	0.0293	-0.0118	-0.0688**	-0.00587
	(0.0364)	(0.0159)	(0.0340)	(0.0201)
Observations	6,581	6,566	6,578	6,566

Note: household sampling weights applied. Regression estimated through a probability model. Estimated coefficients represent average marginal effects. Clustered standard errors at the district level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Source: authors' elaboration from IOF 2019/2020.

Table A17: Heterogeneity analysis - Child level, prevalence of stunting at the district level

Variables	Stunting	Wasting	Underweight	Overweight
2nd Trimester	0.304***	-0.0342*	-0.0403	0.0452**
	(0.0450)	(0.0206)	(0.0366)	(0.0190)
3rd Trimester	0.284***	-0.0145	0.0482	0.00412
	(0.0452)	(0.0194)	(0.0387)	(0.0221)
2nd Trimester* Stunting (average district)	-0.673***	0.0432	-0.0624	-0.0790*
	(0.111)	(0.0426)	(0.0886)	(0.0438)
3rd Trimester* Stunting (average district)	-0.591***	0.0154	-0.174*	0.0404
	(0.114)	(0.0392)	(0.0937)	(0.0624)
Stunting (average district)	0.789***	0.0116	0.230***	0.0157
	(0.0697)	(0.0352)	(0.0705)	(0.0364)
HH size	0.00644**	0.000177	0.00127	-0.000812
	(0.00294)	(0.00150)	(0.00213)	(0.00109)
Female headed HH	0.0295	0.0124*	0.0188	-0.0231**
	(0.0221)	(0.00730)	(0.0166)	(0.00979)
Asset index	-0.0349***	-0.00159	-0.0228***	0.00156
	(0.00584)	(0.00274)	(0.00518)	(0.00187)
Dep. Ratio	0.0134	0.000910	0.0149***	-0.00325
	(0.0103)	(0.00383)	(0.00578)	(0.00416)
% employed	0.0154	-0.000848	0.000551	-0.0201*
	(0.0346)	(0.0137)	(0.0245)	(0.0117)
HH head has primary+ educ.	-0.0224	-0.00647	-0.0148	-0.0193**
	(0.0145)	(0.00655)	(0.0128)	(0.00806)
HH owns land	0.0353	0.00699	0.0154	-0.0142
	(0.0399)	(0.0149)	(0.0353)	(0.0177)
TLUs	-0.00395	-0.00192	0.000121	2.77e-05
	(0.00365)	(0.00186)	(0.000240)	(7.02e-05)
HH is subsistence ag.	-0.00158	0.0101	-0.00325	0.0168*
	(0.0237)	(0.0105)	(0.0150)	(0.00918)
Rural	0.00522	-0.000547	-0.00661	0.0174*
	(0.0209)	(0.00904)	(0.0208)	(0.0103)
HH receives social assistence	-0.0154	0.0385**	0.0206	-0.0208
	(0.0347)	(0.0168)	(0.0398)	(0.0221)
Female	-0.0611***	0.00109	-0.0328**	-0.00394
	(0.0136)	(0.00550)	(0.0138)	(0.00693)
Newborn	-0.224***	0.0411***	-0.0169	-0.00128
	(0.0152)	(0.00546)	(0.0105)	(0.00785)
Firstborn	0.0299	-0.0113	0.0244	0.00385
	(0.0219)	(0.0113)	(0.0175)	(0.0110)
Access to city (in hours)	-0.0101**	-0.00243	-0.00479	0.000511
	(0.00408)	(0.00196)	(0.00354)	(0.00190)
% of land=Savannas	2.35e-05	-0.000139	0.000174	0.000675**
	(0.000654)	(0.000233)	(0.000647)	(0.000283)
% of land=Grasslands	0.000478	4.57e-05	0.000755	0.000379
	(0.000748)	(0.000238)	(0.000649)	(0.000298)
% of land=Broadleaf forest	0.000491	0.000164	0.00122	0.000819
	(0.00129)	(0.000464)	(0.00104)	(0.000535)
% of land=Urban	0.00119	-0.000203	-0.000663	0.000899
	(0.00139)	(0.00116)	(0.00149)	(0.000554)
prov=CD	0.0675	-0.0278	-0.0496	-0.00438
	(0.0467)	(0.0391)	(0.0622)	(0.0204)
prov=NI	0.0421	0.0221	0.00659	0.0145
	(0.0440)	(0.0394)	(0.0647)	(0.0198)
prov=NP	0.0139	-0.0124	-0.0742	0.0357*
	(0.0468)	(0.0409)	(0.0664)	(0.0216)
prov=ZA	0.0247	-0.0230	-0.0321	-0.00479
	(0.0438)	(0.0391)	(0.0644)	(0.0206)

prov=TT	-0.00497	-0.0188	-0.0777	0.00980
	(0.0505)	(0.0410)	(0.0648)	(0.0217)
prov=MA	0.0264	-0.0340	-0.0725	0.00331
	(0.0472)	(0.0401)	(0.0642)	(0.0198)
prov=SF	-0.0154	-0.0163	-0.0669	0.0102
	(0.0486)	(0.0386)	(0.0621)	(0.0211)
prov=IN	-0.0778	-0.0158	-0.0985	0.0208
	(0.0533)	(0.0412)	(0.0602)	(0.0191)
prov=GZ	-0.0509	-0.0141	-0.0948	0.0320
	(0.0500)	(0.0399)	(0.0613)	(0.0222)
prov=MP	-0.203***	-0.0168	-0.0635	0.0112
	(0.0430)	(0.0365)	(0.0490)	(0.0152)
month=February	0.00811	0.00692	0.0140	-0.0176
	(0.0222)	(0.0110)	(0.0203)	(0.0150)
month=July	0.0463*	-0.0177	0.0377*	0.0167
	(0.0261)	(0.0116)	(0.0226)	(0.0116)
month=September	0.0118	0.00312	0.0146	0.00393
	(0.0341)	(0.0129)	(0.0263)	(0.0171)
month=October	-0.0204	0.00932	-0.0114	-0.0165
	(0.0346)	(0.0134)	(0.0213)	(0.0159)
month=December	0.0193	-0.0135	-0.0708**	-0.00485
	(0.0309)	(0.0153)	(0.0335)	(0.0195)
Observations	6,088	6,074	6,085	6,074

Note: household sampling weights applied. Regression estimated through a probability model. Estimated coefficients represent average marginal effects. Clustered standard errors at the district level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Source: authors' elaboration from IOF 2019/2020.