Nutrition transition in the Indian rural-urban interface

Dissertation

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Summary

While economic growth in many low- and middle-income (LMICs) has led to the reduction of poverty and undernutrition, some of these LMICs are undergoing a simultaneous increase in overnutrition and micronutrient deficiency. Urbanization is one of the widely attributed factors for this nutrition transition. However, urbanization in many LMICs is non-linear, messy, and hidden. Due to this, there has been a horizontal and outward growth of cities extending their formal boundaries. This has resulted in the creation of complex rural-urban interfaces at the peripheries of rapidly urbanizing cities. The rural-urban interfaces offer unique opportunities as well as challenges for the food consumption and nutritional status of people. For example, proximity to urban centers facilitates improved access to input, output, and labor markets and enables households to engage in diversified livelihood strategies. This increases average household income. With the increased income individuals and households might consume a diversified diet that is rich in nutritional quality. However, urbanization and globalization of the region might increase the temptation among people to consume energy-dense, fatty, salty foods, and sweetened beverages. In addition, the better infrastructure of the region and livelihood diversification into off-farm employment popularize a sedentary lifestyle among inhabitants of the rural-urban interface. Interactions among all these factors – such as increased income, diversified and globalized diet, and sedentary lifestyle – might lead to a faster transition of the nutrition-related problems from undernutrition to overnutrition in the rural-interface regions. Thus, studying the food consumption pattern and nutritional status of millions of people who live in the rural-urban interfaces might provide important insights into the rapid nutrition transition occurring in many LMICs.

To this end, this dissertation considers the rural-urban interface of Bangalore, a mega-city in southern India, to study individual and household nutrition in the face of the rapid urbanization of the region. For this, the data from a primary socioeconomic survey of 1275 households conducted between December 2016 to May 2017 was used in the empirical analyses. The first two essays presented in this dissertation study how the consumption of diversified diets and the energy-dense processed foods are associated with the nutritional status of individuals. The third essay of this dissertation studies how different livelihood strategies – such as agricultural operations and off-farm employment – are associated with household nutrient consumption adequacy.

The first essay investigates the association of dietary diversity with the anthropometric outcomes of children and women. This relationship is estimated not just at mean but also at different points of the conditional distribution of anthropometric outcomes using the quantile regression method. This estimates whether the relationship between dietary diversity anthropometrics outcomes differs for undernourished vs. overnourished individuals. In addition, the use of six different measures of the individual- and household-level dietary diversity helps to test whether the relationship between dietary diversity and anthropometric outcomes depends on the indicator used. The results of this essay show

that there is no strong and monotonic relationship between dietary diversity and (most) anthropometric outcomes among children and women. A consistent and significant association is found only for overweight/obese children. That is, for these demographics increased dietary diversity is associated with adverse anthropometric outcomes. These results indicate that the increased dietary diversity as a means to improve anthropometric outcomes might not be effective, especially, in those areas facing multiple burdens of malnutrition.

The second essay investigates the relationship between processed foods and obesity. It applies a probit regression model to estimate how the share of calories from the semi- and ultra-processed foods are associated with the prevalence of obesity among women. The results show that excess consumption of calories from semi-processed foods is positively associated with the increased prevalence of obesity among women. This association is stronger for women in lower-income groups in the rural-urban interface of Bangalore. For the high-income groups, the diet correlates of obesity shift towards ultra-processed foods. This shows that the increased risks for obesity are occurring at a lower level of dietary transition in India. This calls for strategic interventions to prevent a rapid increase in the obesity epidemic among lower-income groups in India.

The third essay estimates how the diversification of livelihood strategies affects household nutrition. This essay is particularly interested in estimating the full composite effect of different employment choices – agricultural operations and off-farm employment – on households' nutrient consumption adequacy. It applies a multivariate regression framework to household-level nutrient adequacy ratios of three macronutrients (calories, protein, and fat) and three micronutrients (vitamin A, iron, and zinc). The results show that it is not just either of the employment choices but also different combinations of agricultural operations and off-farm employment that are important to explain household nutrition. The results also imply that the relationship between income generated from different combinations of agricultural operations and off-farm employment and nutrition is non-linear. That is, increased income improves household nutrient consumption in the beginning, however, a further increase in income is associated with overnutrition. Furthermore, undernutrition is most prevalent among socio-economically disadvantaged households.

The findings of these three essays provide important insights into the food consumption and nutritional status in the rural-urban interface regions. The relationships between diets and nutritional status, and the relationship between livelihood strategies and nutrient consumption are mostly non-linear in the context of the rural-urban interface of Bangalore. To understand these intricate relationships it is, thus, necessary to go beyond the mean analysis and study different sub-samples (such as undernourished vs. overnourished, lower-income vs. higher-income, calorie-adequate vs. calorie-inadequate, etc.). This also calls for strategic interventions that follow a double-duty policy action framework to cater to the nutrition-related problems of different subsets of the population in the rural-urban interface regions.

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1. Introduction

1.1. Nutrition transition – Background

Urbanization, globalization, economic growth, and increased income have led to varying degrees of changes in dietary patterns. One of the important consequences of dietary change is the shift in the nutritional problems from undernutrition to overnutrition (Popkin et al., 2012; Popkin, 2009; Shetty, 2002). This is referred to as "nutrition transition" in the literature. The literature identifies five patterns in the nutrition transition: (i) hunting and collecting food, (ii) early agriculture and famine, (iii) end of famine and nutritious diet, (iv) overconsumption and degenerative diseases, and (v) behavioral changes (Popkin, 1993). While the high-income countries are working towards bringing behavioral changes to reduce the prevalence of overnutrition and non-communicable diseases (NCDs) (Cawley, 2015; Jones, 2016; Popkin, 1999), many low- and middle-income countries (LMICs) are rapidly moving from the consumption of traditional to energy-dense diets (Popkin et al., 2012; Popkin, 2009; Popkin and Gordon-Larsen, 2004). Even though nutrition transition is traditionally associated with the higher-income group and urban areas in LMICs (Neuman et al., 2013; Popkin, 2001; Subramanian et al., 2009), recent studies have shown that the rate of transition is fastest among the lower-income group and rural areas (Aiyar et al., 2021; Jones-Smith et al., 2012; Popkin, 2019).

When a country undergoes structural transformation (ST), the share of the workforce and economic output is reallocated from the labor-intensive (e.g. agriculture) to capital-intensive (e.g. industry and service) activities (Herrendorf et al., 2014). This means that there is a shift from physically strenuous to relatively sedentary work. These transitions in occupation patterns from farm to off-farm sectors also increase income (Haggblade et al., 2010; Ogutu and Qaim, 2019). The increase in income leads to greater diversity in the diets – which often extends to include energy-dense foods and beverages – consumed by households and individuals (Pingali, 2007; Rahman and Mishra, 2020). Tempted by taste and convenience, the consumption of energy-dense food items is increasing among all social strata in LMICs (Pingali, 2007). Furthermore, improved access to off-farm employment and rising off-farm wages increase the opportunity cost of preparing food at home (Regmi and Dyck, 2001). This increases the intake of processed and convenient foods outside the home. The increase in the consumption of energy-dense foods accompanied by work-effort transitions due to ST leads to overnutrition (Popkin et al., 2012; Popkin, 2009).

1.2. Rural-urban interface

Urbanization fuels both the shift in occupation patterns to more sedentary work and dietary transition towards consumption of energy-dense food items (Pingali, 2007; Popkin, 2009; Rahman and Mishra, 2020). However, urbanization in many LMICs is non-linear, messy, and hidden (Cohen, 2006; Denis et al., 2012; Steinhübel and Cramon-Taubadel, 2020). This has led to horizontal growth of mega-cities extending their formal borders (Ellis and Roberts, 2015). Furthermore, the spillover effect of urbanization facilitates the emergence of several small towns around the peripheries of big cities (Cohen, 2006; Ellis and Roberts, 2015). Thus, the dynamics of the urban environment are spread over larger geographical areas than the official boundaries of cities, leading to the creation of complex rural-urban interfaces. The urbanization effects in such rural-urban interfaces follow polycentric patterns (Steinhübel and Cramon-Taubadel, 2020). That is, urban influence extends from the big city to surrounding small towns which then spill over into the rural areas (Steinhübel and Cramon-Taubadel, 2020). Households and individuals in the rural-urban interface regions are affected by the proximity to both the mega-city and the small towns around. On one extreme, the economic growth of cities exerts increasing demand for food items, services, and other consumables (Bairagi et al., 2020), which needs to be catered by the agricultural production and labor supply from nearby peri-urban and rural areas (Pribadi and Pauleit, 2015; Rao et al., 2006). On the other extreme, improved access to expanding agricultural input and output markets encourages smallholder farmers in the peri-urban and rural areas to commercialize their agricultural production (Cazzuffi et al., 2020; Rao et al., 2006; Vandercasteelen et al., 2018). In addition, the growing service, industry, and retail sector in the nearby urban centers demand an additional labor force (Christiaensen et al., 2013). Thus, the demand and supply forces due to the proximity to urban centers in the rural-urban interface regions facilitate diversification of livelihood strategies into the farm and off-farm sectors (Steinhübel and Cramon-Taubadel, 2020). The resulting increase in income due to livelihood diversification leads to greater dietary diversity (DD) (Rahman and Mishra, 2020). The rapid expansion of supermarkets and modern food outlets in these regions creates easy access to energy-dense, fatty, salty foods and sweetened beverages, which increases the prevalence of overnutrition (Demmler et al., 2018; Otterbach et al., 2021; Zhou et al., 2015).

It is expected that, by 2050, 68 percent of the world population will be living in cities (United Nations, Department of Economic and Social Affairs, Population Division, 2019). It is likely that the rapidly urbanizing cities in many LMICs follow the non-linear and polycentric urbanization patterns observed for the mega-cities. These trends in urbanization patterns might result in creating many such rural-urban interfaces discussed above. The diverse economic opportunities in these regions might attract a large share of the population in LMICs to reside in the interface regions between rural and urban areas. The factors associated with nutrition transition such as urbanization, diversified and globalized diets, occupation transition, and lifestyle changes in the dynamic environment of the rural-urban interface might contribute to the substantial increase in global overnutrition and NCDs. In addition, the disadvantaged section of the population living in the rural-urban interfaces might be food insecure and face limited access to basic necessities (Ellis and Roberts, 2015; Ruel et al., 2017). Thus, studying the factors associated with food consumption and nutritional outcomes of people living in rural-urban interface regions is important to understand the average increase in the prevalence of malnutrition at the country level.

1.3. Objectives and research questions

Development literature discussing nutrition and health generally considers rural and/or urban areas as distinct entities based on certain criteria such as population density and/or occupation structure. Thus, there are distinct differences in the dietary patterns and nutritional status observed between rural and urban areas (Amugsi et al., 2014; Bren d'Amour et al., 2020; Popkin, 2009, 2001). Due to such differences, it is believed that people living in urban areas are more likely to experience nutrition transition than their counterparts living in rural areas (Popkin, 2009, 2001). As cities – big and small – all over the world grow, it is likely that more and more people find their homes in the rural-urban interface region and get affected by its dynamic surroundings. In such interface region, drawing a line somewhere in between and considering one part as urban and another part as rural to study nutrition and health will obscure the minute details. Only a few authors have used a continuous measure of urbanization to study urbanization and nutrition (Dahly and Adair, 2007; Jones-Smith and Popkin, 2010). They suggest that the relationships between urbanization and nutrition are better explained through the continuous scale than the traditional dichotomous measure of rural and urban.

Among other factors that affect nutrition in the rural-urban interface, this dissertation focuses on understanding the role played by diets and livelihood strategies in individual and household nutrition, respectively. The rapid urbanization and economic growth of the rural-urban interface region provide unique opportunities as well as challenges concerning food consumption and nutritional status. For example, improved agricultural production facilitated by better access to input and output markets in the rural-urban interface region might improve the access to diversified diets rich in nutrient quality. However, the urbanization and globalization of the region might also increase the temptation among people to consume energy-dense processed foods. This means that an individual's choice to consume from a diverse set of food items is likely to be associated with his/her nutritional status. Similarly, proximity to agricultural and labor markets facilitates households to simultaneously engage in agricultural and off-farm employment. Thus, a household's choice to engage in different types of employment influence its ability to produce and purchase food, thus its nutrient consumption.

The literature discussing the relationship between diets and nutritional status can be divided into two strands. The first strand of the literature widely attributes increased DD as a means to improve undernutrition (Agrawal et al., 2019; Pingali et al., 2017). The second strand of the literature suggests decreasing the consumption of energy-dense processed foods to reduce the prevalence of obesity

(Demmler et al., 2018; Popkin, 2017; Shetty, 2002). In the rural-urban interface, individuals are likely to be exposed to both the dietary transition and multiple burdens of malnutrition. In such contexts, whether higher DD is associated with improvements in nutritional status is still an open question. Furthermore, excess consumption of processed foods in these regions, in the absence of mitigating factors, might increase the likelihood of one being obese. Thus, the first objective of this dissertation is to estimate how the consumption of diversified diets and energy-dense processed foods is associated with the nutritional status of individuals (measured in terms of their anthropometric outcomes) in the dynamic environment of the rural-urban interface.

Similar to diets, the literature discussing the relationship between livelihood strategies and nutrition can be divided into two strands. While the first strand of the literature concentrates on the effect of different agricultural operations (subsistence and commercialized production) on nutrition (Cazzuffi et al., 2020; Ecker, 2018), the second strand estimates the relationship between off-farm employment and nutrition (Rahman and Mishra, 2020). In the rural-urban interface, households face trade-offs in decision-making on production (agricultural operations vs. off-farm employment) and consumption (own produced vs. market purchased food) side. These trade-offs are likely to result in complex patterns in the associations between livelihood strategies and household nutrition. Thus, the second objective of this dissertation is to estimate how different livelihood strategies and the interactions between them are associated with household nutrient consumption adequacy in the face of rapid urbanization in the rural-urban interface.

The two objectives of this dissertation revolve around the following three research questions:

1. How does DD is associated with the anthropometric outcomes of children and women in the rural-urban interface?
2. How does the dietary transition to processed food consumption is associated with the prevalence of obesity among women in the rural-urban interface?
3. How does livelihood diversification into farm and off-farm employment is associated with household nutrition in the rural-urban interface?

1.4. Study area, sampling, and data set

The data used in this dissertation is collected under the framework of the research unit FOR2432 “Social-ecological system in the Indian rural-urban interface: Functions, scales, and dynamics of transition” funded by the German Research Foundation (DFG). The main objective of the research unit FOR2432 is to investigate how the social, economical, and ecological factors interact at different stages of urbanization. To achieve this objective, the researchers from different disciplines conduct biophysical, chemical, and socio-economic experiments/surveys in the same region. The interdisciplinary research of the research unit is carried out in the two transects that cut through the rural-urban interface of Bangalore, a mega-city in Southern India (Hoffmann et al., 2017). The first transect extends outwards towards northern Banglaore and the second transect extends towards southwest Bangalore (see Fig. 1.1).

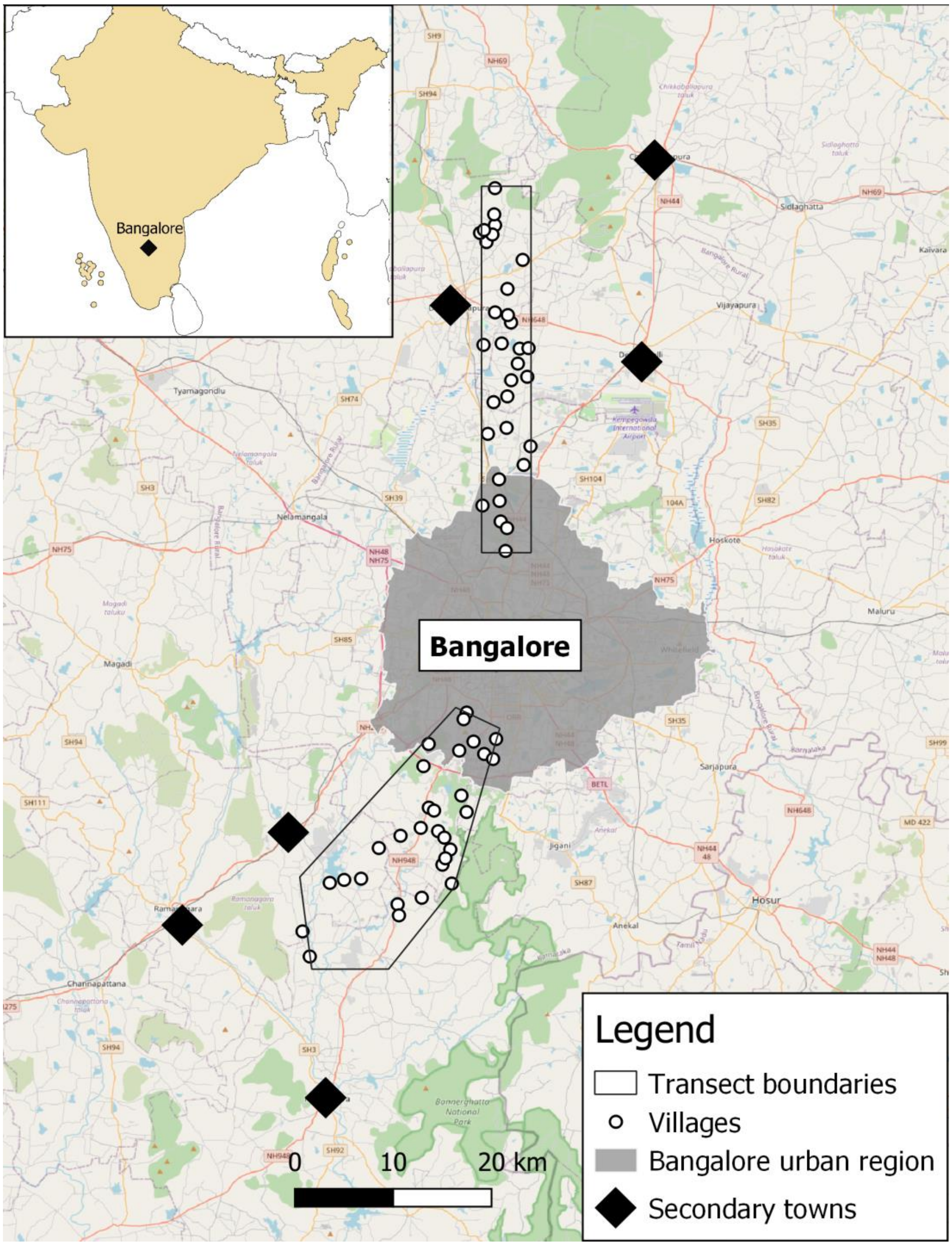

Figure 1.1. Study area, research transects, and the sample households

With a population of 9.6 million (Directorate of Census Operations Karnataka, 2011), Bangalore is the third most populous city in India. It is expected that population growth in Bangalore will reach up to 20.3 million by 2031 (Bharadwaj, 2017). Several small towns located within a 40-kilometer radius and the highways connecting them have led to a rise in urbanization in Bangalore and the surrounding peri-urban area (Directorate of Census Operations Karnataka, 2011). While the industry, service, and information technology (IT) sector is driving rapid urbanization and economic growth of Bangalore city, agriculture and allied activities remain one of the important livelihoods in the peripheries (Directorate of Census Operations Karnataka, 2011; Steinhübel and Cramon-Taubadel, 2020). In addition, several small-scale industries have been set in these peri-urban and rural areas near Bangalore (Directorate of Census Operations Karnataka, 2011). Thus, there are several opportunities for households in this region to engage in diverse income-generating activities. This increases the access and affordability to a variety of food items ranging from unprocessed to ultra-processed in nature, which is again catered by the diverse food markets in the region.

While undernutrition persists, overweight/obesity is the rising health concern in Bangalore (NFHS-5, 2019-20). From the time of data collection and now, we can observe substantial changes in the nutritional status among children and women between the two waves of demographic and health surveys (DHS) in Bangalore (one in 2015-16 and the other in 2019-20) (NFHS-5, 2019-20). That is, within three years underweight and stunting among children below five years has increased by 4 and 11 percent, respectively. At the same time, overweight/obesity among children and women has increased by 22 and 25 percent. The only improvement has been observed in the wasting status of children and thinness among women. These two nutritional outcomes have been reduced by 50 and 40 percent, respectively. In addition, anemia is also a rising health crisis in Bangalore. These statistics indicate that Bangalore is facing multiple burdens of malnutrition. Thus, Bangalore shows the exact patterns in urbanization, occupational transition, and nutrition transition predicted for many LMICs, making it a suitable setting to study the factors associated with the food consumption and nutrition status of people living in its rural-urban interface region.

In the rural-urban interface of Bangalore, a primary socio-economic survey of 1275 households was conducted between December 2016 and May 2017. The sample households were selected following a two-stage stratified random sampling method to represent three stages of urbanization (urban, peri-urban, and rural) in the region (Hoffmann et al., 2017). Using a comprehensive questionnaire, all the sample households were interviewed to collect information on their socio-demographic characteristics and economic activities. The respective caregiver of the households was also interviewed to collect the food consumption data for a 14-day period before the interview. A 24-hour dietary recall data was collected for all children and women in the sample households. In addition, anthropometric measurements such as height and weight were collected for all children below 6 years of age, volunteering children aged between 6 to 14 years, and all women, except pregnant and nursing women, living in the sample households. Using this primary socio-economic survey data, this dissertation tries to understand the role of diets and livelihood strategies in nutrition in the rural-urban interface of Bangalore.

1.5. Outline of the dissertation

This dissertation includes three essays, which are briefly introduced in this section.

Essay 1: A quantile regression analysis of dietary diversity and anthropometric outcomes among children and women in the rural-urban interface of India.[1]

Essay 1 (Chapter 2) addresses the first research question of this dissertation by estimating the association of different DD indicators on anthropometric outcomes of children and women. Increasing the consumption of a diversified diet has been the focus of many nutrition policies around the world to improve anthropometric outcomes of people (National Portal of India, 2018; UNICEF, 2018; WHO, 2020). However, such policies are often not supported by adequate and unambiguous evidence from the empirical literature (Ali et al., 2013; Amugsi et al., 2014; Arimond and Ruel, 2004; Savy et al., 2008). Furthermore, in the context of dietary transition, DD is not just limited to food items that are considered to be rich in nutritional quality (such as fruits, vegetables, animal products, etc.) but extends to include energy-dense, fatty, salty foods, and sweetened beverages. In this case, the relationship between DD and anthropometric outcomes might differ for undernourished vs. overnourished individuals. That is, increased DD might improve the anthropometric outcomes of an undernourished individual; however, for an overnourished individual a further increase in DD might not have a significant improvement and sometimes result in adverse anthropometric outcomes.

To accommodate these requirements, we apply a quantile regression (QR) method to study the association of DD at different quantiles of the conditional distribution of anthropometric outcomes of three demographics in Bangalore (younger children, older children, and women). Anthropometric outcomes are measured using z-scores for children and body mass index (BMI) for women. One of the reasons for ambiguity in the relationship between DD and anthropometric outcomes in the literature is due to the different measures of DD employed (Marshall et al., 2014). Thus, to test the robustness of our estimations, we use six different measures of DD at the individual- and household-level. This also helps to understand whether the relationship between DD and anthropometric outcomes is sensitive to the choice of the measure adopted.

The results of this essay provide evidence on whether or not increasing DD can be used used to measure improvements in the anthropometric outcomes of individuals in regions experiencing urbanization, dietary transition, and multiple burdens of malnutrition.

[1] This essay is written in collaboration with Nitya Mittal, Ashwini B.C., K.B. Umesh, Stephan von Cramon-Taubadel, and Sebastian Vollmer. It is under revise and resubmit in *Food Policy*.

Essay 2: Processed food consumption and peri-urban obesity in India.[2]

Essay 2 (Chapter 3) addresses the second research question of this dissertation on how dietary transition into the consumption of processed foods is associated with the prevalence of obesity among women. The dietary transition towards the intake of energy-dense, fatty, salty foods and sweetened beverages is one of the widely attributed factors for the global rise in obesity. Literature explaining the rising prevalence of obesity in India attributes this to the proximity to the nearby urban centers, transitions in the occupation patterns, and socio-economic status of the people (Aiyar et al., 2021; Dang et al., 2019; Meenakshi, 2016; Subramanian et al., 2011; Subramanian et al., 2009). However, due to a lack of detailed dietary data, the role of dietary transition into processed foods in obesity is not adequately explored in India. Production of processed foods is the outcome of multiple levels of industrial processing, which can be either semi-processed or ultra-processed (Monteiro et al., 2013). The urban influence from the mega-city Bangalore and the nearby small towns on the rural-urban interface of Bangalore provides easy access to both semi- and ultra-processed foods. Furthermore, occupation transitions in the rural-urban interface might popularize a more sedentary lifestyle among people. All these factors increase the likelihood of one being obese in the rural-urban interface than the ones living in the hinterlands.

In many LMICs, semi-processed foods such as sugar and oil are considered luxury foods and they generally dominate everyday diets (Bairagi et al., 2020; Colen et al., 2018). Thus, an increase in income might increase the consumption of semi-processed foods, especially among lower-income groups. In India, semi-processed foods are more affordable because they are made available at relatively cheaper prices through the public distribution system (PDS) (Government of Karnataka, 2013). Whereas consumption of ultra-processed foods might be common among higher-income groups because they have to be purchased at market prices. Furthermore, there might be a higher opportunity cost of cooking food among the higher-income group. This might also make them consume higher quantities of ultra-processed foods, as they are easy to prepare at relatively less time. Both of these scenarios are likely to be observed in the rural-urban interface regions that are in the middle of ST. Thus, it is important to understand whether it is the semi-processed or the ultra-processed foods that are driving the average increase in the prevalence of obesity in the rural-urban interface of Bangalore. In the empirical analysis, we model how the share of calories consumed from semi- and ultra-processed foods increases the prevalence of obesity (BMI≥25) among women.

[2] This essay is written in collaboration with Anaka Aiyar and Stephan von Cramon-Taubadel.

This is essay is published as a working paper in the Department of Agricultural Economics and Rural Development of the University of Göttingen with a slightly modified name – “Dietary transition and its relationship with socio-economic status and peri-urban obesity”.

The results of this essay help to identify diet correlates of obesity in the rapidly urbanizing region of India. Knowing key drivers of obesity for different segments of the population help to develop interventions targeting those that are at the greater risk of obesity due to the consumption of food items that undergo different levels of industrial processing.

Essay 3: You eat what you work – livelihood strategies and nutrition in the Indian rural-urban interface.[3]

Essay 3 (Chapter 4) addresses the third research question of this dissertation by estimating the relationship between livelihood strategies and household nutrient consumption adequacy. It is well established that diversification of livelihood choices brings positive improvements to the living standards of smallholder households (Haggblade et al., 2010; Ogutu and Qaim, 2019). However, there appear to be complex patterns in the relationship between livelihood strategies and nutrition. For example, increased on-farm production diversity is found to increase DD (Ecker, 2018). However, this relationship becomes weaker when the households shift to commercialized agricultural operations (Sibhatu et al., 2015). The off-farm employment was found to increase the household's expenditure on diversified diet and improve nutrition security (D'Souza et al., 2020; Rahman and Mishra, 2020). Since households face trade-offs in decision-making on the production (labor allocation to agricultural vs. off-farm employment) and consumption side (consuming own produced vs. market purchased food) in the rural-urban interface, the likely effect on their nutrition consumption would be complex. To account for such complex patterns we propose a conceptual framework, which builds on the recent work by Muthini et al. (2020), to estimate the full composite effect of livelihood strategies on nutrition.

Due to the improved access to agricultural and labor markets, the livelihood of most households in the rural-urban interface can be assumed to lie somewhere in between the two extremes of a continuous scale. Where one extreme indicates pure agricultural operations and another extreme indicates pure off-farm employment. Share of either of livelihood dimensions will decide how much of the food consumed is from own production and how much is consumed from market purchases. This helps to understand how different combinations of agricultural operations and off-farm employment affect nutrition when households are exposed to urbanization and dietary transition.

In the empirical analysis, we apply a multivariate regression framework with the household-level nutrient adequacy ratios (HNARs) for three macronutrients (calories, proteins, and fat) and three micronutrients (vitamin A, iron, and zinc) as dependent variables. When households experience dietary transition, the tendency to consume energy-dense, fatty, salty foods and sweetened beverages increases. Such a dietary pattern increases the consumption of macronutrients (especially calories and

[3] This essay is written in collaboration with Linda Steinhübel. It is under review in *World Development.*

fat) at the cost of important micronutrients. Thus, HNARs of individual nutrients help to measure household nutrient consumption in a nuanced way. In our regression analysis, we allow for the interactions between different agricultural operations and off-farm employment, which helps to quantify their full composite effect on nutrition.

The results of this essay help to identify complex patterns in the relationship between livelihood strategies and nutrition when households are exposed to urbanization, dietary transition, and rural transformation. Understanding these complex patterns help to update the interventions that target food systems to prevent malnutrition in LMICs.

The remainder of the dissertation is structured as follows. The three essays of this dissertation are presented in chapter 2 to 4. Chapter 5 summarizes the main conclusions of the three essays and discusses limitations and ideas for future research.

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2. A quantile regression analysis of dietary diversity and anthropometric outcomes among children and women in the rural-urban interface of India

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Abstract

Based on a primary survey conducted in the rural-urban interface of Bangalore, this study contributes to the understanding of the nature of the relationship between Dietary Diversity (DD) and anthropometric outcomes of young children (<6 years) (measured by weight-for-age (WAZ), height-for-age (HAZ) and weight-for-height (WHZ) z-scores), older children (6-14 years) (measured by BMI (Body Mass Index) z-scores) and women (15 years and above) (measured by BMI) in the Indian context. We examine this association not just at the mean, but also at different points of the conditional distribution of anthropometric outcomes using the Quantile Regression (QR) method. We use six different measures of individual- and household-level DD to check whether the estimated association depends on the choice of metric used. Our results show that increased DD is associated with higher z-scores at the upper quantiles of WAZ distribution for younger children and BMI z-scores distribution for older children. This reflects an adverse effect of increased DD on anthropometric outcomes among overweight/obese children. Except for these two, no other associations at any other quantile for any anthropometric outcome of young children, older children, and women are consistently significant for various measures of DD. Our results suggest that policies focusing on improving DD might not be effective in improving (most) anthropometric outcomes especially in the areas facing multiple burdens of malnutrition. Thus, there is a need for further exploration of DD and anthropometric outcomes in the context of malnutrition.

Keywords: Dietary Diversity, Anthropometric outcomes, Quantile Regression, India, Urbanization

2.1. Introduction

The adverse effects of malnutrition among children on their physical and cognitive development and thereby on their economic and social achievements, quality of life, and mortality are well known (Hoddinott et al., 2008; Martorell, 1999; Strauss and Thomas, 1998; Victora et al., 2008). In addition, malnutrition among adolescent girls and women leads to poor reproductive health and thus affects morbidity and mortality in the next generation as well. Despite concentrated efforts, undernutrition remains a big challenge for the Indian government. Though reductions in the prevalence of undernutrition have been observed in past decades, the rates are still high. According to the latest available data, 38 percent of Indian children under the age of five are stunted, 36 percent are underweight, and 21 percent are wasted (NFHS-4, 2015-16). Besides, India is now also facing the burden of overnutrition: while 23 percent of women are underweight, 21 percent are overweight (NFHS-4, 2015-16). The prevalence of overweight among women has doubled over the past decade.

Among various factors that contribute to better anthropometric outcomes, nutritious food is considered to play an important role. Improved DD, a proxy for higher micronutrient intake, has been widely advocated by many studies (Agrawal et al., 2019; Aiyar et al., 2021; Corsi et al., 2016; Gausman et al., 2018; Kim et al., 2017; Pingali et al., 2017) as a means to improve anthropometric outcomes. Even in policy-making, it is widely accepted that a diverse diet is crucial for better health outcomes. Improving DD has been the focus of many health policies in India and around the world. ***Poshan Abhiyaan***, the latest initiative of the Indian government to improve anthropometric outcomes, also focuses on improving DD, among other key nutrition strategies (National Portal of India, 2018). Improved DD as a means to improve anthropometric outcomes is emphasized by WHO (2020) and UNICEF (2018).

However, such policies are often not supported by adequate and unambiguous evidence from the empirical literature. Several studies examine the relationship between DD measures and anthropometric outcomes, but there does not seem to be robust evidence in support of a positive relationship between the two. While some studies (Darapheak et al., 2013; Frempong and Annim, 2017; Rah et al., 2010) find that increasing DD is associated with better anthropometric outcomes, the results vary considerably across age groups (Arimond and Ruel, 2004; Perkins et al., 2018; Saaka and Osman, 2013) and locations (urban/rural) (Amugsi et al., 2014; Arimond and Ruel, 2002; Hatløy et al., 2000). In addition, many studies do not find any significant relationship between DD and anthropometric outcomes (Ali et al., 2013; Luna-González and Sørensen, 2018; McDonald et al., 2015; Miller et al., 2020). Similar ambiguities are observed for the relationship between DD and anthropometric outcomes among women (McDonald et al., 2015; Saaka and Osman, 2013; Savy et al., 2008). Nevertheless, it is safe to conclude that a positive relationship is context-specific and should not be generalized.

Consequently, when framing nutrition policies in India it is imperative to consider evidence for the Indian population. Unfortunately, the evidence from India is scarce and the nature of the relationship between DD and anthropometric outcomes is not well studied. To the best of our knowledge, there are only a few relevant studies (Borkotoky et al., 2018; Corsi et al., 2016; Kim et al., 2017; Menon et al., 2015; Beckerman-Hsu et al., 2020; Chandrasekhar et al., 2017; Nithya and Bhavani, 2018, 2016). The first four studies focus on young children and find that increasing DD is associated with a lower prevalence of undernutrition. However, these studies all use the same data set – NFHS 2005-06. Only three studies use more recent state-level data. In Maharashtra, higher DD is associated with lower odds of stunting and being underweight among children aged 6-23 months (Chandrasekhar et al., 2017). The other two studies examine different demographic groups of the same household in Maharashtra and Odisha (Nithya and Bhavani, 2018, 2016). They do not find a significant association of DD with BMI of school-aged children and adolescents. A robust relationship is observed only for adult BMI. Thus, there are only a few recent studies for India, and these provide mixed results. Besides, none of these studies consider overnutrition, a growing concern in India.

To examine the relationship between DD and anthropometric outcomes, one requires a comprehensive dataset with information on both individual food intake and anthropometric outcomes. Limited availability of such datasets, except for NFHS could be one of the reasons for the scant literature in India. While many studies collect information on household consumption expenditure, large datasets on individual intake are scarce. Such data are even scarcer for children above the age of six; this age group has received little attention in the literature.

This provides the context for our study. We examine the relationship between DD and anthropometric outcomes for three different demographics in Bangalore, a city in South India, and contribute to the sparse literature for India. Our rich dataset, collected through a primary survey, provides information on anthropometric outcomes of – young children (<6 years) (measured by WAZ, HAZ; and WHZ z-scores); older children (6-14 years) (measured by BMI z-scores); and women (15 years and above) (measured by BMI). 31 different specifications for DD measures have been used in the literature (Marshall et al., 2014). The ambiguity in results may be driven by the use of different metrics. Our extensive dataset allows the use of several different measures of DD to examine whether the relation between DD and anthropometric outcomes is sensitive to the choice of DD measure. We use individual-level 24-hour dietary recall and 14-day household food consumption data to construct six different measures of DD. This is not possible for many studies, including NFHS data.

Our study contributes to the literature in two ways. First, we focus on a unique setting that has received little consideration not only in India but globally – the rural-urban interface. Most of the literature considers rural and/or urban areas as distinct entities that are defined according to some criteria such as population density. However, given the fast-paced growth and urbanization in India and elsewhere, there are many areas where the boundaries between rural and urban are not clearly defined. In such areas, a gradient of urbanization is a more relevant measure. Studies from China show that the relationship between urbanization and health is better explained using a continuous measure of urbanization than an arbitrary rural/urban dichotomy (Dahly and Adair, 2007; Jones-Smith and Popkin, 2010). The peri-urban zone surrounding Bangalore city, which we define as the rural-urban interface, is one such example. This interface is a highly dynamic environment in which households are exposed to diverse dietary opportunities in the form of access to a wide variety of foods that might increase DD. However, globalization and urbanization might also lead to temptations in the form of what is sometimes referred to as a 'westernized diet', i.e. higher intakes of energy, saturated fat, sodium, and sugar that might lead to overnutrition and, consequently a higher incidence of obesity and diet-related non-communicable diseases. Therefore, increasing DD in such a setting might have different implications for the anthropometric outcomes of different individuals. These areas may experience a much faster shift to what Barry M. Popkin's study in 1993 refers to as stage four of nutrition transition than the far-off rural areas (Popkin, 1993).

Second, none of the studies discussed above considers whether the relationship between DD and anthropometric outcomes differs for under-nourished vs. over-nourished individuals. While a positive relationship between DD and weight at lower quantiles of weight distribution implies an improvement in anthropometric outcomes, a positive relationship at higher quantiles may imply increased incidence of overweight or obesity and thus deterioration in anthropometric outcomes. To our knowledge, there are very few papers that investigate the heterogeneity in the association between DD and anthropometric outcomes (Amugsi et al., 2017; Amugsi et al., 2016). We apply a QR method in this study to understand the heterogeneity in the relationship.

The focus on improving DD in nutrition policies in India does not seem to be backed by sufficient empirical evidence. Additionally, current policies only target undernutrition and do not account for overnutrition, which is an increasing health issue in India. The relationship between higher DD and overnutrition is not well understood for India due to the lack of empirical evidence. Further research on the relationship between DD and anthropometric outcomes in India is therefore imperative. The results of this study will contribute to a better understanding of the nature of the relationship between DD and anthropometric outcomes in the Indian rural-urban interface and contribute to evidence-based policy-making.

2.2. Study area and Data

2.2.1. Sampling design

The empirical analysis is based on a primary socio-economic survey conducted in the rural-urban interface of Bangalore in the state of Karnataka in December 2016 – May 2017. This survey is part of a larger German-Indian collaborative project on the social-ecological implications of urban expansion. The survey covers 1275 households from two transects cutting through the rural-urban interface of Bangalore, one to the north and the other to the southwest. Fig. 2.1 shows the research area and sample villages. A two-stage stratified random sampling design was used to select the sample households. In the first stage, all the villages in each transect were divided into six strata using the "Survey Stratification Index (SSI)" (Hoffmann et al., 2017). Then, villages were randomly selected from each stratum proportional to their size, 61 villages in total. Further, using the village households' list, sample households were again randomly selected proportional to the size of the village.

The survey collected information on the household food consumption for the past 14 days and individual 24-hour dietary recall data for all three age groups considered. Height and weight were measured for all children below 6 years, volunteering children from 6 to 14 years, and all women aged 15 years and above in the household.

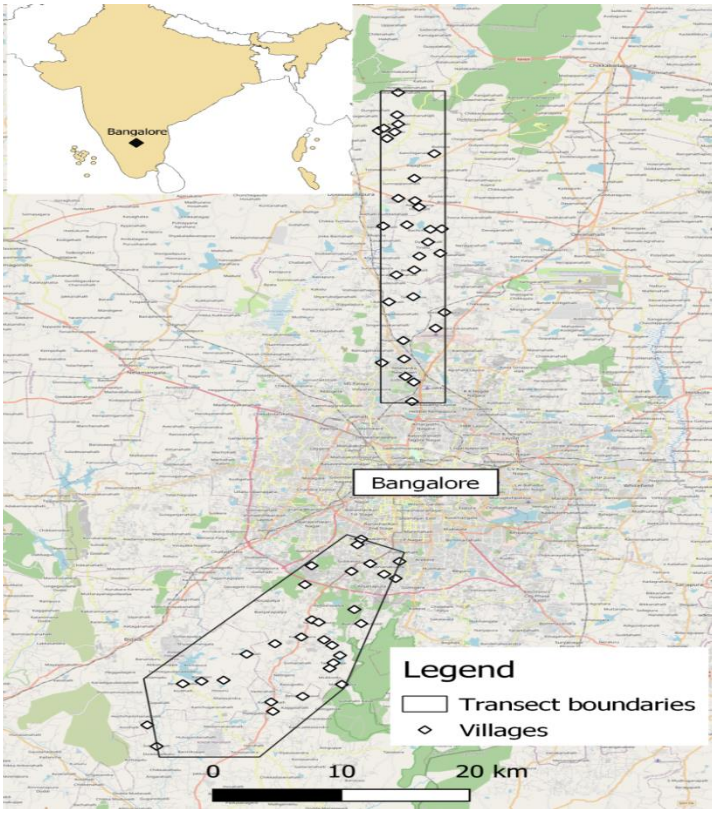

Figure 2.1. Research area, transects, and sample villages

2.2.2. Variable definition

Using the anthropometric measurements, we calculate–WAZ, WHZ, and HAZ z-scores for young children, BMI z-scores for older children, and BMI for women. These are the outcome variables in our analysis.

Studies often use household-level DD measures as an indicator of individual-level DD. However, the intra-household distribution of resources is not always equitable, and anthropometric outcomes are ultimately affected by individual intakes and not household availability (Gupta et al., 2020). We, therefore, construct both household- and individual-level DD measures to compare if our results vary between the two. Household food consumption and individual dietary recall data are used to construct the household- and individual-level DD measures, respectively, which are our main explanatory variables.

The first set of measures we calculate is the **Dietary Diversity Scores (DDS),** which is constructed by a simple count of different food groups consumed. Household Dietary Diversity Score (HDDS), constructed using 14-day food consumption data, ranges from 0-12. At the individual-level, DDS is constructed using 24-hour dietary recall data. For younger children, all food items are divided into 8 groups (Swindale and Bilinksy, 2006), and for women into 9 groups (Kennedy et al., 2011). They are called Children's Dietary Diversity Score (CDDS) and Women's Dietary Diversity Score (WDDS), respectively. As there is no specific measure of individual DDS for older children, we use the same food groups as in HDDS. We call this Individual Dietary Diversity Score (IDDS).

The second set of measures, **Food Variety Scores (FVS),** is a simple count of different food items consumed in a specific recall period. These scores are again calculated at both the household- and individual-level. Household food consumption data allows us to calculate two additional measures – **Food Consumption Score (FCS)** (INDEX Project, 2018) and **Mean Micronutrient Adequacy Ratio (MMAR)**. While HDDS is a simple count of the number of food groups consumed, FCS is a more nuanced metric that is calculated as a weighted average using the frequency of consumption of the food groups. MMAR is the average of adequacy ratios for ten micronutrients (calcium, iron, vitamin A, vitamin B6, vitamin C, zinc, thiamin, riboflavin, niacin, and folate). To summarize, we use two individual-level and four household-level DD measures.

2.2.3. Missing data

Though repeated visits were made to collect anthropometric data for younger children, we were unable to collect information for 113 children (29 percent). After accounting for missing data and outliers, our sample consists of 198, 188, and 189 observations for WAZ, WHZ, and HAZ, respectively. To ensure that there is no sample selection bias; we compare the characteristics of children for whom data are missing with those for whom we have complete data using logistic regressions (Appedndix 2.1). We find that children with missing data have younger and less educated mothers. We control for these characteristics in our estimation. For older children participation in the anthropometric survey was voluntary, and 66 percent of these children chose to participate. Logistic regression results show that participation in the survey by children in this age group is not driven by any socio-economic characteristics and that data are missing at random (Appendix 2.2). A similar analysis was done for 67 percent of our sample women, for whom the anthropometric information was available. The results show that women for whom data are missing are younger, less educated, have additional jobs, belong to households with lower family size, and live further away from Bangalore city (Appendix 2.3). We account for these characteristics in our analysis.

2.3. Empirical methods

OLS examines the relationship between the dependent and the explanatory variable at the mean. It is not an appropriate technique for those outcomes for which the expected relationship varies along the distribution. Using QR, the relationship can be estimated not only at the mean but over the entire conditional distribution of the outcome variable (Koenker and Bassett, 1978).

For children (both young and older), we include the following control variables – (i) child characteristics (age and gender); (ii) maternal characteristics (mother's age, education, height, and occupation); and (iii) household characteristics (family size, caste, religion, economic status, gender of the primary decision-maker, access to sanitation facilities and safe drinking water, and agricultural household). In the regression estimation for women, the explanatory variables are – (i) women characteristics (age, education, occupation, number of children, marital status); and (ii) household characteristics (same as for children). We also control for transect fixed effects. The household distance to Bangalore city center is included as a continuous measure of urbanization. In addition, we include the interaction of DD measures with age and gender of the child, and the distance to Bangalore city center.

The estimation equation used for the multivariate QR analysis is therefore as follows:

$$y = \beta_{0\tau} + \beta_{DD\tau}DD + \beta_{1\tau}X_1 + \beta_{2\tau}X_2 + \beta_{3\tau}X_3 + \beta_{4\tau}X_4 + e_\tau \qquad (2.1)$$

where y is the outcome variable, $\beta_{DD\tau}$ is the quantile-specific coefficient of interest that quantifies the association between DD and respective anthropometric outcome. We examine the relationship at 5th, 10th, 25th, 50th, 75th, 90th, and 95th quantiles of the anthropometric outcome. X_1, X_2, and X_3 are the vectors of individual-, maternal-, and household-level characteristics. X_2 is included in estimates for children but not for women. X_4 includes the distance to Bangalore city center and transect fixed effects.[4]

2.4. Summary statistics

Table 2.1 presents the descriptive statistics for the sample of three different age groups studied. Among younger children, 25 percent are underweight, 35 percent are stunted, and 17 percent are wasted. The mean BMI z-scores for older children is -0.83, and the average BMI for women is 23.53. While individual DDS show low DD, average HDDS is much higher. There is a substantial difference between individual- and household-level measures, which justifies our decision to study both. Other household-based DD measures also suggest higher DD in sample households.[5]

Table 2.1. Descriptive statistics – Average anthropometric outcomes and dietary diversity measures

VARIABLE	Unit	Younger children	Older children	Women
Weight-for-age (WAZ)	Continuous	-1.06 (1.58)		
Underweight	Percentage	25		
Height-for-age (HAZ)	Continuous	-1.28 (2.03)		
Stunted	Percentage	35		
Weight-for-Height (WHZ)	Continuous	-0.37 (1.83)		
Wasted	Percentage	17		
BMI z-scores	Continuous		-0.83 (1.67)	
BMI	Continuous			23.53 (5.1)
CDDS/IDDS/WDDS	Count	4.8 (0.8)	7.8 (1.5)	3.6 (0.8)
Individual FVS	Count	30 (11.4)	29 (11.6)	23 (10.7)
HDDS	Count	10.4 (1.1)	10.5 (0.9)	10.3 (1.1)
FCS	Continuous	92.6 (12.7)	91.5 (12.5)	91 (14.1)
Household FVS	Count	48 (12.5)	47 (12)	46 (12)
MMAR	Continuous	0.81 (0.1)	0.81 (0.17)	0.83 (0.16)

Notes: Standard errors in parentheses.

In Table 2.2, we present average DD by nutritional status of the child. Here as well, average individual-level DD measures are lower than the household-level DD measures. Some DD measures indicate that undernourished children have lower DD than well-nourished children. Similarly, Table 2.3 presents differences in DD by the nutritional status of older children and women. Among older children (in panel (a)), some measures of DD indicate lower DD among undernourished children than

4 We present results for the most parsimonious model for each anthropometric outcome using the Likelihood-ratio test.

5 Appendix 2.4 summarizes the socio-economic characteristics of the sampled households.

among well- and over-nourished children. Among women (in panel (b)), only household FVS varies significantly among the three groups.

Table 2.2. Dietary diversity measures by the anthropometric outcome of younger children

Variables	The anthropometric outcome of the children: Underweight	Normal weight	Difference
CDDS	4.6 (0.1)	4.9 (0.05)	-0.3 (0.13)**
Individual FVS	29 (1.5)	31(0.7)	-1.5 (1.73)
HDDS	10.1 (0.19)	10.6 (0.06)	-0.4 (0.18)**
FCS	87 (2.2)	94 (0.7)	-6.6 (2.3)**
Household FVS	43 (1.6)	49 (0.8)	-6 (1.85)***
MMAR	0.8 (0.02)	0.83 (0.01)	-0.02 (0.02)
Percentage of children	24	76	
	Stunted	Not stunted	
CDDS	4.7 (0.1)	4.8 (0.1)	-0.1 (0.1)
Individual FVS	29 (1.2)	31 (0.8)	-1.9 (1.5)
HDDS	10.4 (0.1)	10.5 (0.1)	-0.1 (0.15)
FCS	91 (1.6)	94 (0.9)	-3 (1.8)*
Household FVS	45 (1.2)	50 (1.0)	-5 (1.61)***
MMAR	0.79 (0.02)	0.84 (0.01)	-0.04 (0.02)*
Percentage of children	36	64	
	Wasted	Not wasted	
CDDS	4.7 (0.1)	4.8 (0.05)	-0.1 (0.18)
Individual FVS	29 (1.6)	30 (0.7)	-1 (1.8)
HDDS	10.2 (0.2)	10.5 (0.06)	-0.3 (0.3)
FCS	89 (3.3)	93 (0.7)	-4 (3.4)
Household FVS	46 (2.5)	48 (0.8)	-2 (2.6)
MMAR	0.80 (0.03)	0.83 (0.01)	-0.2 (0.3)
Percentage of children	16	84	

Notes: Standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1

Table 2.3. Dietary diversity measures by the anthropometric outcome of older children and women

Variables	BMI z-scores for Older Children: Thin (BMI z-score<=-2)	Normal weight (-2<BMI z-score<1)	Overweight (BMI z-score>=1)
IDDS	7.8 (0.13)	7.7 (0.09)	8 (0.12)
Individual FVS	30 (0.97) [c]	29 (0.67) [b]	33 (1.66) [b,c]
HDDS	10.4 (0.1) [a]	10.6 (0.05) [a]	10.4 (0.11)
FCS	90 (1.11)	92 (0.63)	90 (1.52)
Household FVS	45 (1.2) [a]	48 (0.7) [a]	48 (1.5)

MMAR	0.8 (0.01)	0.83 (0.01) [b]	0.78 (0.02) [b]
Percentage of children	24	61	15
	BMI for Women		
	Thin (BMI <18.5)	Normal weight (18.5<=BMI<25)	Overweight or obese (BMI >=25)
WDDS	3.5 (0.06)	3.7 (0.03)	3.6 (0.04)
Individual FVS	23 (0.74)	23 (0.42)	23 (0.49)
HDDS	10.3 (0.07)	10.3 (0.04)	10.4 (0.04)
FCS	90 (0.78)	90 (0.53)	91 (0.60)
Household FVS	43 (0.81) [a,c]	45 (0.49) [a,b]	47 (0.55) [b,c]
MMAR	0.82 (0.01)	0.83 (0.01)	0.84 (0.01)
Percentage of women	15	48	36

Notes: Standard errors in parentheses. [a] – 5% significance difference between column 2 and 3; [b] – 5% significance difference between column 3 and 4; [c] – 5% significance difference between column 4 and 2.

2.5. Results

2.5.1. OLS results

We first present the results for all DD measures using the OLS method for young children, older children, and women. Detailed OLS regression results for one of the DD measures – individual DDS – are presented in the second column of Tables 4 to 8, and the estimated effects of different DD measures are summarized in Fig. 2.2. We find that only the two individual-level DD measures (CDDS and individual FVS) are associated with the WAZ scores for younger children, that is, increasing DD is associated with higher WAZ scores. There are no significant associations for other outcomes and age groups.

2.5.2. QR results

The QR results for all DD measures are presented in Fig. 2.3 to 2.7 for the anthropometric outcomes of younger children, older children, and women. While some of the regression models include interactions with DD variables, the Figures only show the main effect of DD on anthropometric outcomes. We present detailed QR results for one of the six measures of DD used in the study – individual DDS – in columns 3 to 9 of Tables 2.4 to 2.8.[6]

[6] Results of regressions that use the other five measures of DD for both OLS and QR methods are available from the authors.

Younger Children

WAZ scores

Fig. 2.3 shows that increasing DD is associated with higher WAZ scores. Individual DD measures – CDDS and individual FVS – have significant positive coefficients at the bottom three and middle two quantiles of WAZ distribution, respectively. The positive coefficients indicate that increasing DD increases WAZ scores for young children. However, household-level measures do not show a significant relationship in these quantiles. Besides, individual FVS, FCS, and household FVS have a significant positive coefficient at 95th quantile. Since children in the 95th quantile of WAZ distribution have higher than recommended weight, the positive coefficient indicates that increased DD increases the prevalence of overweight/obesity. We also include an interaction variable between DD measures and distance to Bangalore city. The coefficient for the direct effect of household distance to Bangalore city on WAZ is significant and positive at the 95th quantile, implying higher WAZ scores among children living further away from Bangalore city. The coefficient of the interaction variable is significantly negative at the 95th quantile, which indicates that increased DD is associated with lower WAZ scores in areas farther away from Bangalore city. Given the prevalence of overweight/obesity in this quantile, these associations indicate that while the incidence of overweight/obesity increases among children living further away from Bangalore city, increased DD decreases the prevalence of overweight/obesity among these children.

HAZ scores

In Fig. 2.4, we present the association between DD measures and HAZ scores for younger children. Only two of the six measures of DD, both household-level measures (household FVS and MMAR), have significant and positive coefficients at some quantiles of the HAZ distribution. The coefficients are significant at the 25th and 50th quantile for household FVS and at the 75th quantile for MMAR. It suggests that an increase in DD is associated with higher HAZ scores, implying an improvement in the height-based anthropometric outcome. However, the evidence is not robust for different measures of DD. The estimation model includes an interaction term between DD measures and gender. While the coefficient of the dummy variable for boys is positive at 95th quantile for three of the four household measures of DD, the coefficients for interaction between this dummy variable and DD measures are negative at the same quantile for the same DD measures. Though positive coefficients at the 95th quantile of HAZ indicate better anthropometric outcome for boys, an increase in DD at this quantile is associated with poorer anthropometric outcome for boys compared with girls.

WHZ scores

Fig. 2.5 presents the results for WHZ scores of younger children. Two of the six measures of DD (CDDS and FCS) have a positive coefficient at the 50^{th} quantile of the WHZ scores. Apart from this, household FVS and FCS have positive coefficients at 25^{th} and 75^{th} quantile, respectively. These positive coefficients indicate that increased DD is associated with higher WAZ scores. In addition, increasing individual FVS is associated with lower WHZ scores at the 95^{th} quantile. This is a desirable result at this quantile of the weight-based anthropometric outcome, and it is in contrast to the results observed for WAZ. All these effects at the respective quantiles imply that an increase in DD is associated with improved WHZ outcome for younger children. However, these results are not robust for different DD measures. We also include an interaction term between DD and the age of the child. The age of a child has a negative coefficient at the 95^{th} quantile of WHZ distribution. However, the interaction term has a positive coefficient at the 95^{th} quantile for three of the six DD measures. Considering that the children in the 95^{th} quantile of WHZ distribution are overweight/obese, these coefficients show that while the increase in the age of children is associated with an improvement in WHZ anthropometric outcome, increasing DD is associated with worse anthropometric outcomes for older children in this age group.

Other covariates

For brevity, we only discuss those covariates which have robust results (that is significant coefficients for at least four out of six DD measures and two of three anthropometric outcomes of younger children). Among other covariates, age of the child has a significant association with all three anthropometric outcomes discussed above. Older children are more likely to have healthier outcomes at lower quantiles of HAZ distribution and upper quantiles of WAZ and WHZ distribution. As is generally observed, gender is an important factor in this context as well. Boys tend to have higher z-scores in upper quantiles than girls. While higher z-scores in top quantiles of the HAZ distribution imply better health, higher z-scores in the top quantiles of the weight-based outcome, WHZ, are not desirable. Compared with non-agricultural households, children from agricultural households are found to have better anthropometric outcomes at the 95^{th} quantile of the WAZ and HAZ distribution, and worse outcomes at lower quantiles of the WHZ distribution. Access to sanitation facilities is associated with higher z-scores at the top quantiles of WAZ and WHZ, implying worsening of anthropometric outcomes among overweight/obese children.

Older Children – BMI z-scores

In Fig. 2.6, we present the association between DD and BMI z-scores in older children. Three of the six measures of DD (IDDS, individual FVS, and household FVS) have positive coefficients at the 95^{th}

quantile of BMI z-scores suggesting that increasing DD is associated with a higher probability of being overweight/obese for this age group. IDDS and individual FVS have positive coefficients at the 90th and 75th quantile of BMI z-scores as well; however, this association is not robust for other DD measures. Since none of the interaction effects were significant for BMI z-scores, none were included in the final specification discussed here.

Among individual characteristics, we find that boys have higher BMI z-scores at upper quantiles, which indicates that boys have a higher probability of being overweight/obese than girls in this age group. Increases in the mother's education are associated with lower BMI z-scores at the 10th quantile, implying that better-educated mothers have a higher probability of having underweight children. Among household characteristics, higher economic status is associated with higher BMI z-scores at lower quantiles. As is also observed for younger children, access to sanitation is associated with higher BMI z-scores at the 95th quantile. The household distance to Bangalore city center has a negative coefficient in the first three quantiles of BMI z-scores indicating poorer anthropometric outcome among this cohort in rural areas.

Women – BMI

We present the results for BMI of women in Fig. 2.7. WDDS has a significant and negative coefficient at the 90th and 95th quantile of the BMI distribution. Since the women in the upper quantiles of BMI distribution are overweight/obese, the negative coefficient indicates that an increase in DD decreases the incidence of overweight/obesity. Apart from this, increases in individual FVS and household FVS are associated with higher BMI at the 75th quantile. However, as with other anthropometric outcomes for children, we find that these associations are not robust for different DD measures. We include an interaction term between DD and distance to Bangalore city center. The coefficient for the direct effect of the distance variable is negative at the 25th, 90th, and 95th quantiles, implying that women who live further away from Bangalore city have lower BMI. The coefficient of the interaction variable is positive at the 90th and 95th quantiles for WDDS and negative for individual FVS and household FVS at the 75th quantile. All these interaction effects at respective quantiles of BMI distribution indicate that increasing DD is not associated with improved anthropometric outcome among women living further away from Bangalore city center. However, these associations are not robust for all measures of DD.

Among women's characteristics, the coefficients for age and age squared are positive and negative, respectively. This implies that increasing age is associated with increasing BMI but at a decreasing rate. Unmarried women have lower BMI than married women in the 95th quantile, implying better health (less overweight/obesity). Women engaged in labor-intensive occupations have lower BMI than housewives at the 25th, 75th, and 90th quantiles, which is not surprising given the differences in the level of physical activities. This is supported by the finding of the difference between housewives and women engaged in office work, both of which are comparatively sedentary activities in this context. Women with more children have higher BMI at the 50^{th}, 75^{th}, and 90^{th} quantiles. Among household characteristics, women belonging to the OBC caste category have higher BMI at middle quantiles than women belonging to the General caste category. We also observe higher BMI for households with higher economic status, households that have access to sanitation (at the 10^{th} to 75^{th} quantiles), and households that have access to safe drinking water (at the 95^{th} quantile). Additionally, women living in the northern transect of the research area have higher BMI at the 90^{th} quantile.

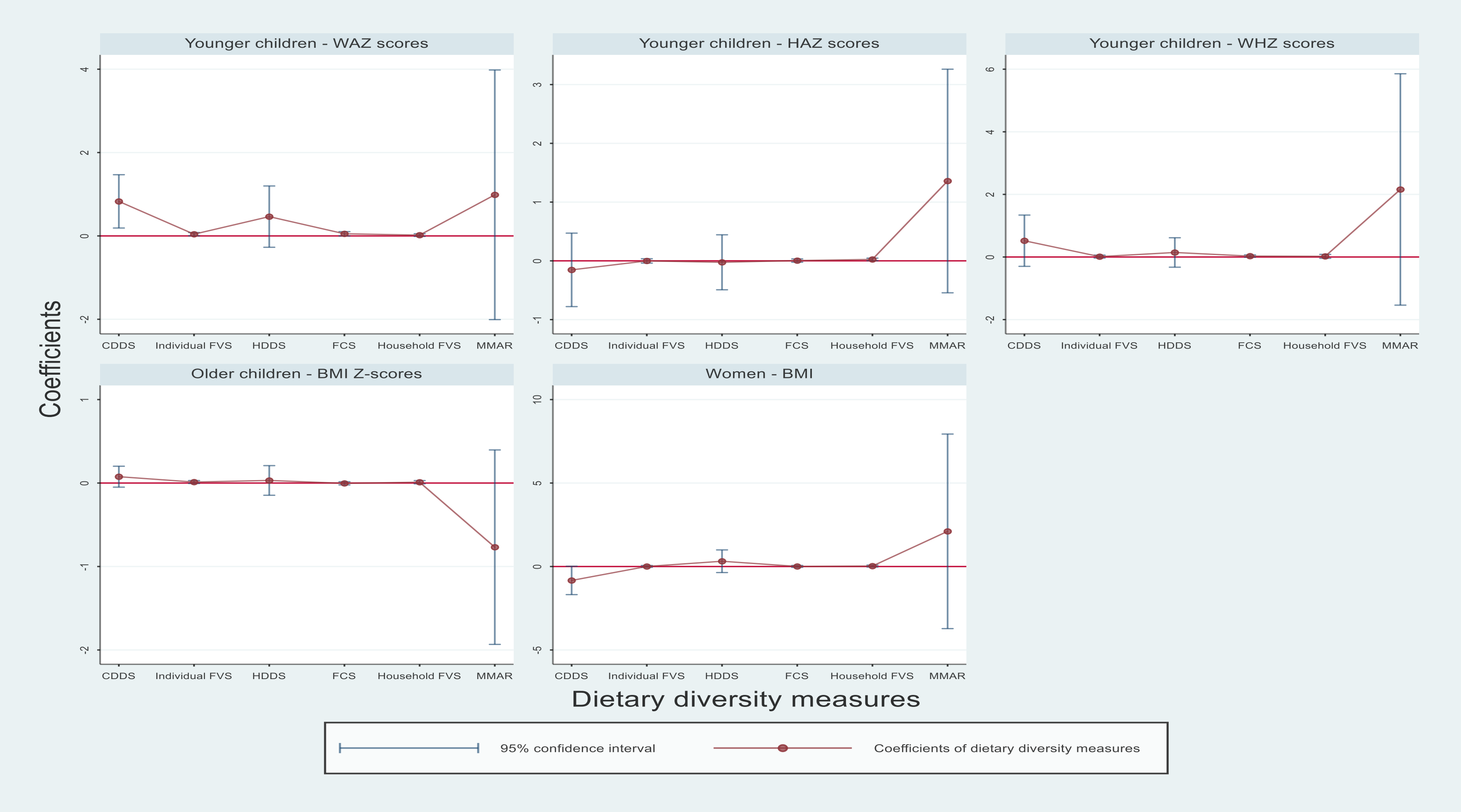

Figure 2.2. Association between anthropometric outcomes and different measures of dietary diversity – OLS regression results for younger children below six years, older children between 6-14 years, and women aged 15 years and above

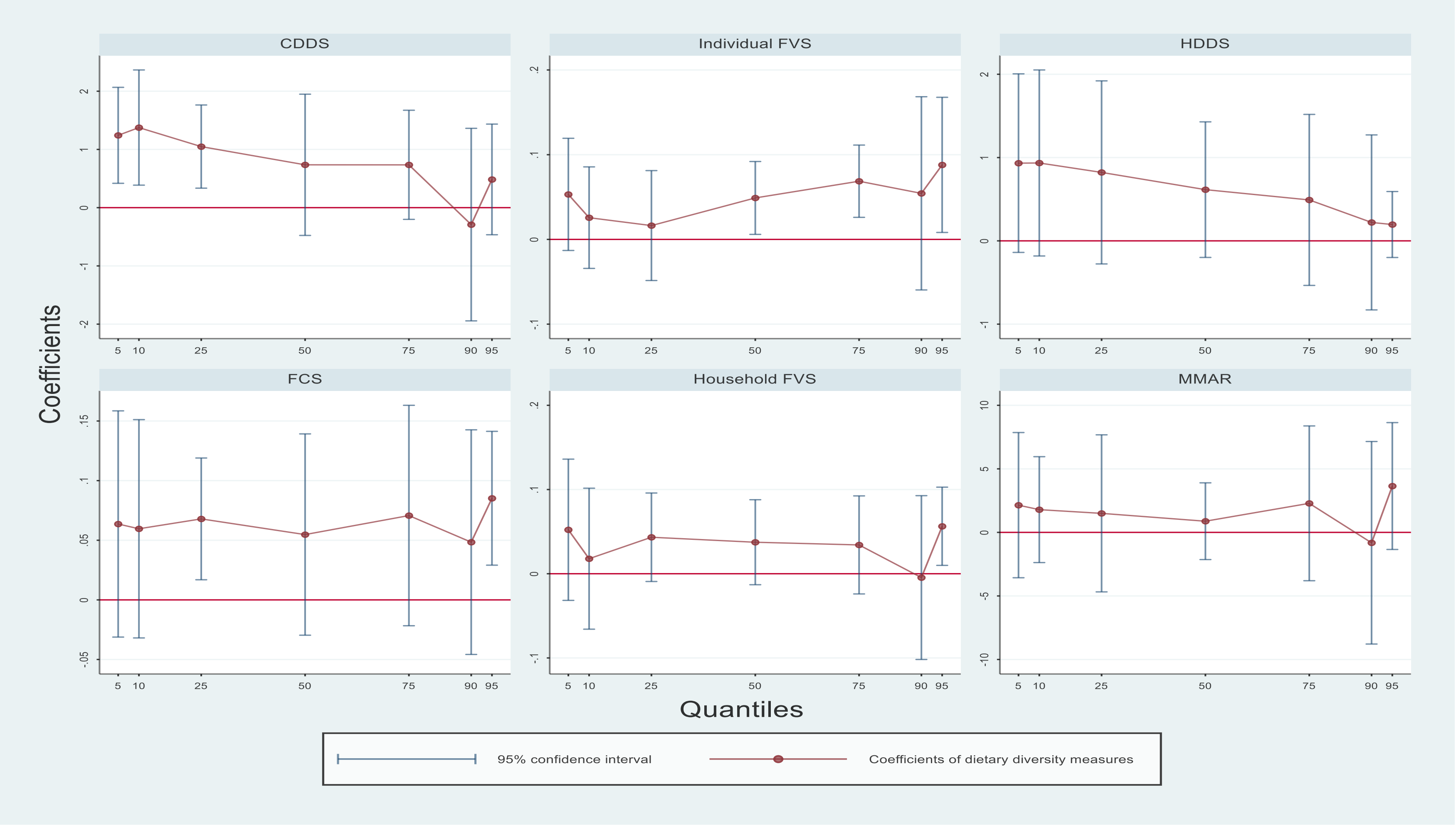

Figure 2.3. Association between WAZ z-scores and different measures of dietary diversity – quantile regression results for children below six years

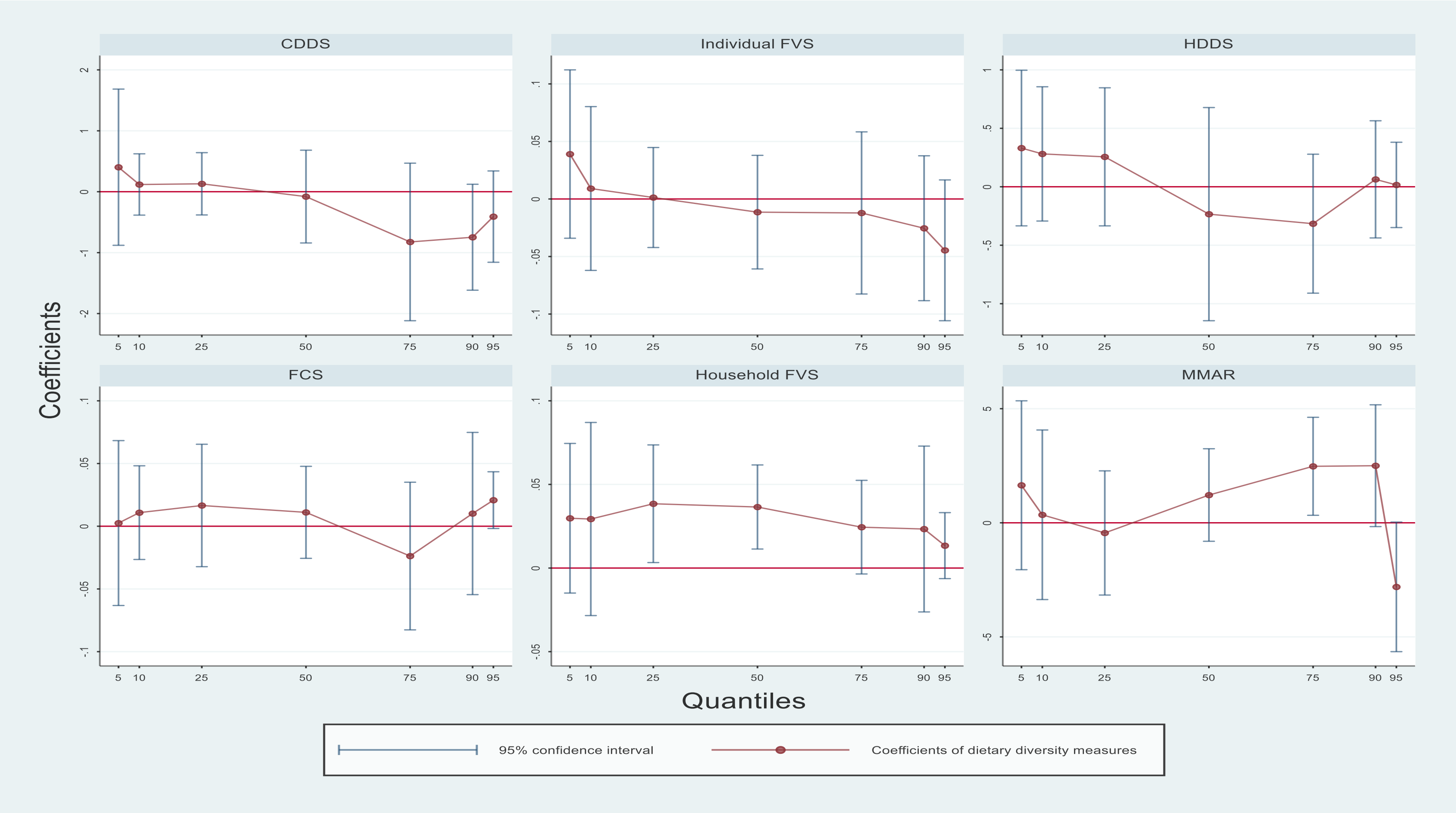

Figure 2.4. Association between HAZ z-scores and different measures of dietary diversity – quantile regression results for children below six years

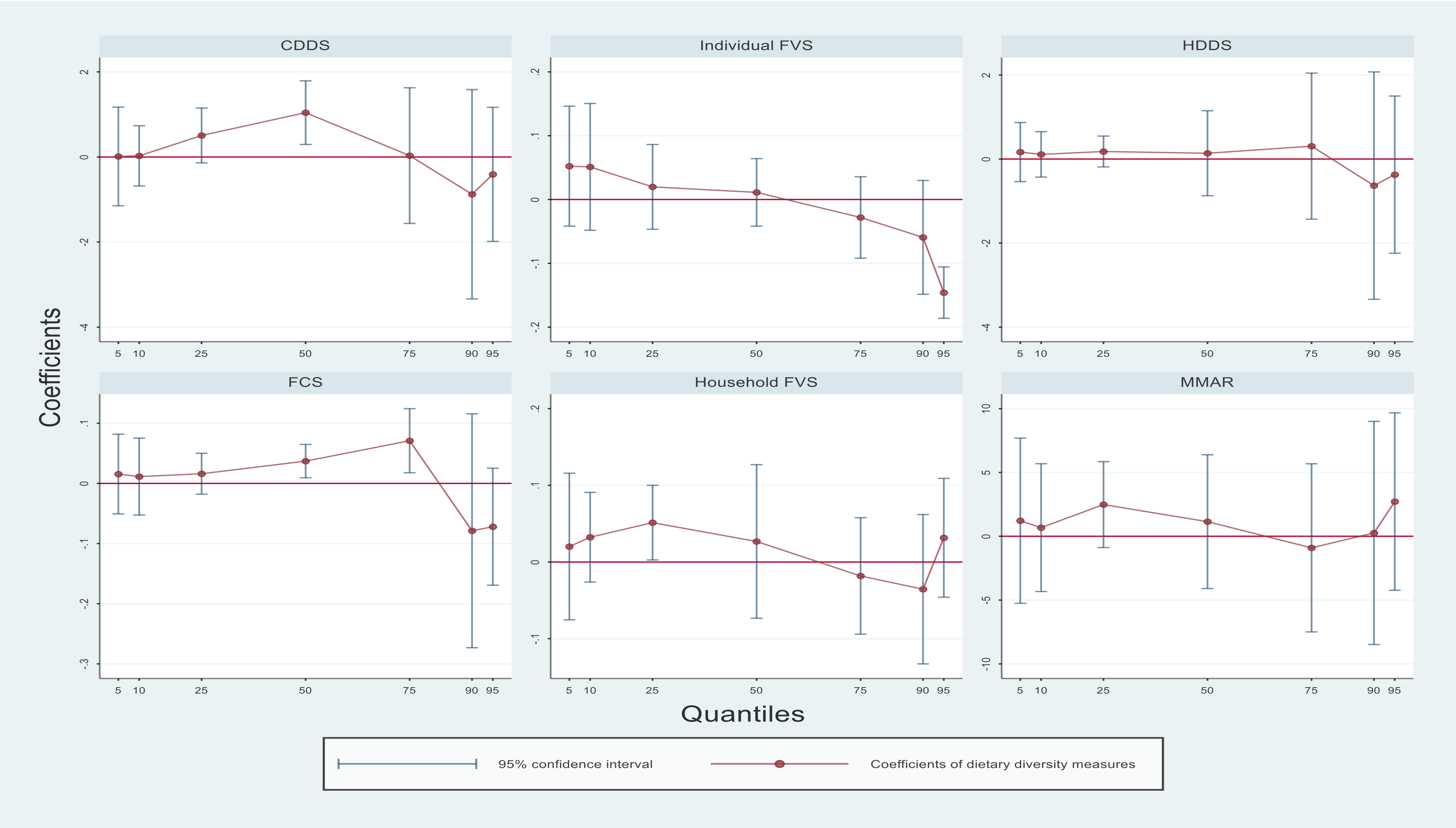

Figure 2.5. Association between WHZ z-scores and different measures of dietary diversity – quantile regression results for children below six years

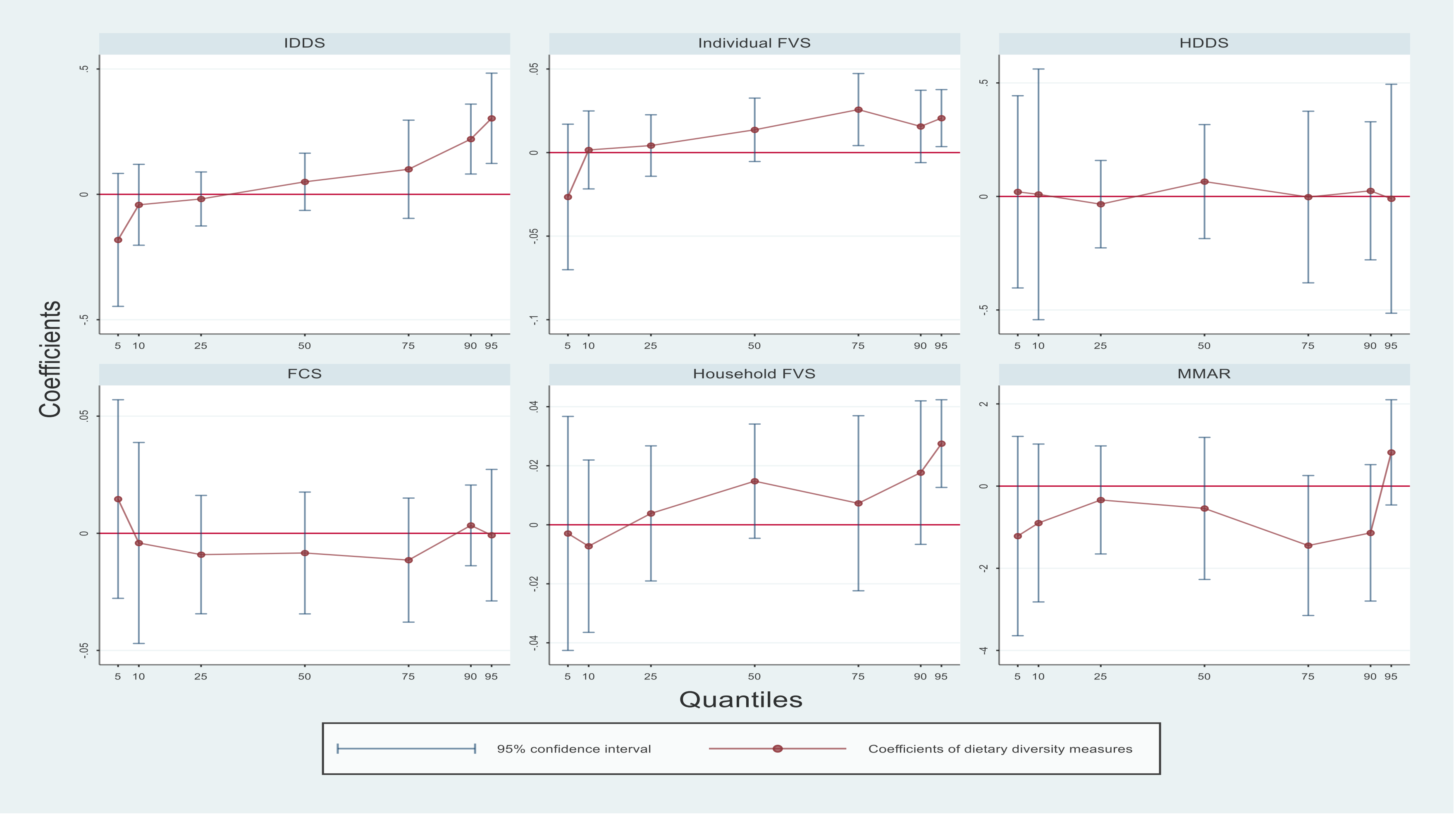

Figure 2.6. Association between BMI z-scores and different measures of dietary diversity – quantile regression results for children between 6-14 years

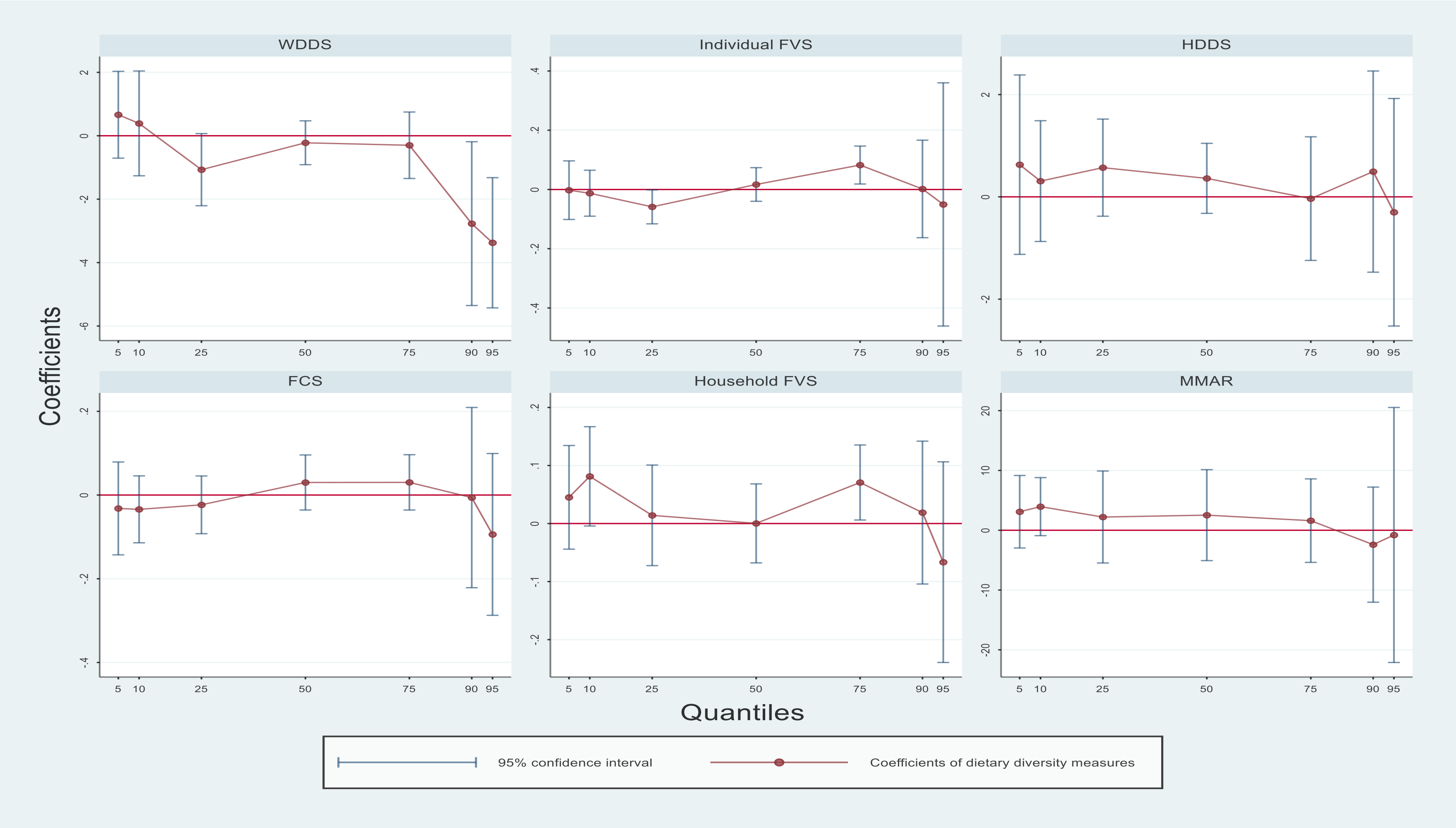

Figure 2.7. Association between BMI and different measures of dietary diversity – quantile regression results for women aged 15 years and above

Table 2.4. Association between CDDS and WAZ z-scores – OLS and quantile regression results for children below six years

Variables	Unit	OLS	Quantile Regression						
			5th	10th	25th	50th	75th	90th	95th
CDDS	Count	0.83**	1.24***	1.38***	1.05***	0.74	0.74	-0.29	0.49
		(0.32)	(0.42)	(0.50)	(0.36)	(0.62)	(0.48)	(0.84)	(0.48)
Distance	Kilometer	0.12*	0.20**	0.19*	0.15**	0.12	0.14	-0.11	-0.02
		(0.07)	(0.09)	(0.10)	(0.07)	(0.11)	(0.13)	(0.16)	(0.11)
Distance*CDDS		-0.02*	-0.04**	-0.04**	-0.03**	-0.02	-0.03	0.02	0.00
		(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.03)	(0.03)	(0.02)
Gender	1=Male	0.03	-0.08	0.12	0.20	-0.03	-0.19	-0.00	0.34
		(0.20)	(0.34)	(0.32)	(0.25)	(0.22)	(0.33)	(0.35)	(0.29)
Age	Years	-0.17**	-0.14	-0.14	-0.16	-0.08	-0.16*	-0.27***	-0.12**
		(0.07)	(0.14)	(0.11)	(0.11)	(0.10)	(0.09)	(0.08)	(0.06)
Mother's education	Years	0.02	0.05	-0.03	-0.02	-0.01	0.07	0.11**	0.11***
		(0.04)	(0.14)	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.03)
Mother's height	Centimeter	0.00	0.03	0.03	0.03	-0.00	-0.00	-0.06*	-0.02
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.01)
Mother's occupation	1=Working	-0.14	0.44	0.74	-0.27	-0.09	-0.24	0.16	1.63***
		(0.34)	(0.36)	(0.47)	(0.34)	(0.44)	(0.82)	(0.53)	(0.38)
HH size	Count	0.03	-0.05	0.03	0.03	0.11	0.03	0.01	-0.07
		(0.06)	(0.09)	(0.14)	(0.09)	(0.07)	(0.05)	(0.10)	(0.06)
Caste	Ref: 1. General								
	2. SC&ST	-0.24	0.12	0.13	-0.25	-0.30	0.03	-0.39	-0.52**
		(0.24)	(0.50)	(0.36)	(0.36)	(0.32)	(0.41)	(0.42)	(0.26)
	3. OBC	-0.07	-0.05	0.16	0.04	-0.34	-0.06	0.12	0.45
		(0.25)	(0.40)	(0.37)	(0.29)	(0.37)	(0.46)	(0.32)	(0.38)
Economic status	Continuous	0.29	-0.17	0.31	0.46*	0.53*	0.13	-0.22	0.31
		(0.25)	(0.56)	(0.44)	(0.27)	(0.29)	(0.51)	(0.39)	(0.22)
Economic status square	Continuous	-0.01	0.01	-0.01	-0.02	-0.02	-0.01	-0.00	-0.03***
		(0.01)	(0.03)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)
Agricultural household	1=Yes	-0.17	0.44	0.33	-0.07	-0.49	-0.29	-0.12	-0.51**
		(0.27)	(0.42)	(0.56)	(0.34)	(0.34)	(0.29)	(0.29)	(0.21)
Decision maker gender	1=Male	-0.32	0.38	0.32	-0.77*	-0.50	-0.16	-0.30	0.47**
		(0.26)	(0.87)	(0.56)	(0.40)	(0.37)	(0.34)	(0.35)	(0.18)
Mother decision maker[a]	1=Yes	-0.16	0.49	0.47	-0.32	-0.75	-0.11	-0.47	0.12
		(0.44)	(1.21)	(0.72)	(0.56)	(0.68)	(0.42)	(0.73)	(0.32)
Sanitation	1=Yes	0.44	0.10	0.49	-0.34	0.57	0.89	1.20	1.63***
		(0.46)	(1.21)	(0.87)	(0.53)	(0.51)	(0.66)	(0.74)	(0.30)
Transect	1=Northern	0.01	0.22	-0.01	-0.09	-0.12	-0.20	-0.37	0.07
		(0.16)	(0.54)	(0.32)	(0.28)	(0.20)	(0.35)	(0.42)	(0.25)
Constant		-6.64**	-13.33***	-15.43***	-11.69***	-7.31	-4.94	12.67*	-0.34

	(2.73)	(4.20)	(4.24)	(3.85)	(4.83)	(4.04)	(7.14)	(3.26)
Observations	198	198	198	198	198	198	198	198
R-squared	0.123	0.032	0.045	0.089	0.087	0.087	0.018	0.013

Notes: [a] – When the mother and the decision maker of the household is same; CDDS – Children's Dietary Diversity Score; Robust standard errors in parentheses ***p<0.01, **p<0.05, *p<0.1

Table 2.5. Association between Children's Dietary Diversity Score (CDDS) and HAZ z-scores – OLS and quantile regression results for children below six years

Variables	Unit	OLS	Quantile Regression						
			5th	10th	25th	50th	75th	90th	95th
CDDS	Count	-0.15	0.40	0.12	0.13	-0.08	-0.82	-0.75*	-0.41
		(0.31)	(0.65)	(0.26)	(0.26)	(0.39)	(0.66)	(0.44)	(0.38)
Gender	1=Male	-1.64	2.15	-1.83	-2.53	-1.00	-5.01	-2.66	0.30
		(1.69)	(4.31)	(1.64)	(2.08)	(2.62)	(3.84)	(3.48)	(4.56)
Gender*CDDS		0.42	-0.38	0.49	0.59	0.30	1.06	0.66	0.26
		(0.33)	(0.86)	(0.34)	(0.40)	(0.53)	(0.70)	(0.64)	(0.91)
Age	Years	0.13	0.49**	0.28***	0.24**	0.08	0.01	0.11	0.41**
		(0.10)	(0.23)	(0.10)	(0.10)	(0.13)	(0.13)	(0.12)	(0.17)
Mother's height	Centimeter	0.03	0.06	0.03	0.04	0.02	0.02	-0.00	0.01
		(0.02)	(0.05)	(0.02)	(0.02)	(0.04)	(0.04)	(0.03)	(0.03)
HH size	Count	-0.06	0.12	0.03	-0.01	-0.04	-0.12	-0.20	-0.24
		(0.07)	(0.09)	(0.08)	(0.06)	(0.12)	(0.13)	(0.21)	(0.20)
Religion	1=Hindu	-0.33	-1.08	-0.18	-0.05	-0.38	-1.03	-0.03	1.12
		(0.52)	(1.77)	(0.50)	(0.41)	(0.92)	(0.64)	(0.65)	(0.79)
Caste	Ref: 1. General								
	2. SC&ST	-0.44	0.33	-0.43	-0.29	-0.52	-0.65	-1.02**	-2.01***
		(0.28)	(0.75)	(0.36)	(0.33)	(0.39)	(0.42)	(0.45)	(0.49)
	3. OBC	-0.05	0.13	-0.41	-0.67	0.07	0.08	0.62	0.44
		(0.49)	(0.96)	(0.45)	(0.54)	(0.60)	(0.99)	(2.07)	(0.98)
Economic status	Continuous	0.03	0.02	0.04	0.05	0.08	0.06	-0.05	-0.09
		(0.06)	(0.16)	(0.08)	(0.08)	(0.09)	(0.10)	(0.13)	(0.21)
Agricultural household	1=Yes	0.89**	0.46	0.53	0.90**	0.78	1.24***	0.98**	1.19***
		(0.35)	(0.63)	(0.46)	(0.41)	(0.49)	(0.42)	(0.47)	(0.40)
Sanitation	1=Yes	0.26	0.06	0.57	0.95	-0.72	-0.50	0.83	1.21
		(0.53)	(0.58)	(0.77)	(0.77)	(0.70)	(0.79)	(0.56)	(0.97)
Distance	Kilometer	-0.03*	-0.02	-0.03	-0.04*	-0.02	-0.03	-0.09***	-0.07**
		(0.02)	(0.04)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Constant		-4.81	-16.33*	-9.83***	-10.88***	-4.62	1.78	7.23	2.64
		(3.81)	(9.11)	(3.05)	(4.19)	(6.16)	(7.04)	(4.53)	(5.03)
Observations		188	188	188	188	188	188	188	188
R-squared		0.102	0.030	0.076	0.074	0.083	0.073	0.038	0.047

Notes: Robust standard errors in parentheses ***p<0.01, **p<0.05, *p<0.1; CDDS – Children's Dietary Diversity Score

Table 2.6. Association between Children's Dietary Diversity Score (CDDS) and WHZ z-scores – OLS and quantile regression results for children below six years

Variables	Unit	OLS	Quantile Regression						
			5th	10th	25th	50th	75th	90th	95th
CDDS	Count	0.52	0.01	0.03	0.51	1.04***	0.03	-0.88	-0.41
		(0.41)	(0.59)	(0.36)	(0.33)	(0.38)	(0.81)	(1.26)	(0.80)
Age	Years	0.04	-0.70	-0.52	0.13	0.79	-0.67	-2.20	-2.61***
		(0.56)	(1.00)	(0.48)	(0.46)	(0.60)	(1.07)	(1.66)	(0.97)
Age*CDDS		-0.05	0.15	0.12	-0.04	-0.21*	0.08	0.37	0.41**
		(0.11)	(0.20)	(0.11)	(0.10)	(0.12)	(0.22)	(0.30)	(0.19)
Gender	1=Male	0.30	0.37	0.24	0.21	0.21	0.04	1.03**	0.37
		(0.21)	(0.44)	(0.29)	(0.28)	(0.25)	(0.45)	(0.49)	(0.30)
Mother's education	Years	-0.03	-0.06	-0.08	-0.06	-0.01	0.05	0.06	-0.01
		(0.06)	(0.10)	(0.05)	(0.07)	(0.06)	(0.09)	(0.09)	(0.04)
Mother's age	Years	0.02	-0.00	0.01	-0.01	0.01	-0.00	0.00	0.08*
		(0.03)	(0.04)	(0.03)	(0.03)	(0.06)	(0.16)	(0.07)	(0.04)
Mother's height	Centimeter	0.01	-0.05	-0.03	-0.01	-0.00	0.02	-0.03	0.10***
		(0.02)	(0.04)	(0.03)	(0.03)	(0.01)	(0.03)	(0.04)	(0.02)
Religion	1=Hindu	0.97**	0.02	0.25	0.48	0.53	0.99	1.28	3.31***
		(0.38)	(0.57)	(0.41)	(0.55)	(0.46)	(1.36)	(0.93)	(0.46)
Caste	Ref: 1. General								
	2. SC&ST	-0.07	-0.75	-0.47	-0.35	-0.08	0.18	0.36	0.66
		(0.32)	(0.62)	(0.38)	(0.36)	(0.40)	(1.50)	(0.52)	(0.57)
	3. OBC	0.25	-0.04	-0.24	0.15	0.48	-0.07	0.61	0.62
		(0.29)	(0.65)	(0.32)	(0.52)	(0.32)	(0.95)	(0.45)	(0.39)
Economic status	Continuous	-0.02	0.03	0.11*	-0.02	-0.01	-0.07	-0.07	-0.24***
		(0.05)	(0.12)	(0.07)	(0.06)	(0.06)	(0.11)	(0.14)	(0.08)
Agricultural household	1=Yes	-0.68**	-1.23*	-1.00**	-0.65**	-0.69**	-0.35	-0.46	0.29
		(0.31)	(0.67)	(0.40)	(0.28)	(0.32)	(1.23)	(1.00)	(0.36)
Own house	1=Yes	0.08	0.37	0.51	0.59*	-0.14	-0.49	-0.96	-1.02***
		(0.36)	(0.70)	(0.38)	(0.34)	(0.42)	(1.08)	(0.66)	(0.28)
Sanitation	1=Yes	1.05*	0.40	0.72	1.32	1.22**	0.91	0.37	0.83*
		(0.58)	(1.16)	(0.62)	(0.83)	(0.62)	(1.36)	(0.86)	(0.45)
Distance	Kilometer	-0.00	0.04	0.01	-0.02	0.00	-0.02	-0.04	-0.06***
		(0.01)	(0.03)	(0.02)	(0.02)	(0.02)	(0.05)	(0.04)	(0.02)
Constant		-5.23*	3.86	0.14	-2.97	-6.25***	-3.17	11.02	-11.80*
		(2.92)	(6.54)	(4.70)	(4.06)	(2.40)	(10.18)	(10.45)	(6.17)
Observations		189	189	189	189	189	189	189	189
R-squared		0.122	0.023	0.038	0.084	0.106	0.076	0.053	0.047

Notes: Robust standard errors in parentheses ***p<0.01, **p<0.05, *p<0.1; CDDS – Children's Dietary Diversity Score

Table 2.7. Association between Individual Dietary Diversity Score (IDDS) and BMI z-scores – OLS and quantile regression results for older children aged 6-14 years

Variables	Unit	OLS	Quantile Regression						
			5th	10th	25th	50th	75th	90th	95th
IDDS	Count	0.08	-0.18	-0.04	-0.02	0.05	0.10	0.22***	0.30***
		(0.06)	(0.14)	(0.08)	(0.05)	(0.06)	(0.10)	(0.07)	(0.09)
Gender	1=Male	0.11	-0.04	0.10	-0.07	-0.08	0.25	0.48	0.33
		(0.18)	(0.32)	(0.28)	(0.24)	(0.19)	(0.32)	(0.30)	(0.23)
Age	Years	-0.00	-0.01	-0.01	-0.05	0.00	0.03	0.02	-0.06
		(0.04)	(0.20)	(0.09)	(0.05)	(0.05)	(0.07)	(0.07)	(0.05)
Mother's education	Years	-0.06*	-0.07	-0.09**	-0.06**	-0.04	-0.08	-0.03	-0.05
		(0.03)	(0.06)	(0.04)	(0.03)	(0.03)	(0.05)	(0.05)	(0.06)
Mother's age	Years	-0.01	-0.05	-0.01	0.01	0.01	0.01	-0.00	0.01
		(0.03)	(0.19)	(0.05)	(0.02)	(0.04)	(0.04)	(0.02)	(0.02)
Mother's height	Centimeter	0.00	-0.00	-0.01	0.02	0.01	-0.01	0.00	-0.02
		(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)	(0.02)
Mother's occupation	1=Working	0.32	0.66*	0.34	0.46*	0.44*	0.18	0.04	0.46
		(0.21)	(0.38)	(0.35)	(0.26)	(0.24)	(0.34)	(0.70)	(0.36)
Caste	Ref: 1. General								
	2. SC&ST	0.17	0.37	0.57*	0.17	-0.19	0.19	0.20	-0.10
		(0.24)	(0.32)	(0.30)	(0.29)	(0.25)	(0.41)	(0.44)	(0.30)
	OBC	0.24	0.12	0.63**	0.30	0.10	0.19	0.10	0.26
		(0.25)	(0.45)	(0.32)	(0.29)	(0.32)	(0.42)	(0.47)	(0.30)
Economic status	Continuous	0.14***	0.28**	0.18*	0.16***	0.14**	0.17**	0.04	0.06
		(0.05)	(0.14)	(0.09)	(0.04)	(0.06)	(0.08)	(0.09)	(0.08)
Own house	1=Yes	0.31	0.04	0.33	0.33	0.19	-0.03	0.26	0.48*
		(0.24)	(0.65)	(0.46)	(0.29)	(0.27)	(0.47)	(0.40)	(0.29)
Safe drinking water	1=Yes	-0.09	-0.28	-0.34	-0.35	-0.26	0.17	0.56	-0.08
		(0.36)	(0.76)	(0.48)	(0.40)	(0.42)	(0.42)	(0.43)	(0.82)
Sanitation	1=Yes	0.13	0.17	-0.45	-0.01	0.22	0.96*	0.75	1.32***
		(0.38)	(1.67)	(0.60)	(0.54)	(0.43)	(0.52)	(1.02)	(0.25)
Distance	Kilometer	-0.03***	-0.07***	-0.05***	-0.03***	-0.02*	-0.02	-0.03	-0.02*
		(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
Transect	1=Northern	0.06	0.48	0.56*	-0.00	-0.06	-0.24	0.29	0.38
		(0.19)	(0.36)	(0.33)	(0.23)	(0.20)	(0.31)	(0.32)	(0.26)
Constant		-2.20	0.01	-0.20	-5.49*	-3.67	-1.14	-2.27	1.27
		(2.82)	(6.76)	(3.84)	(3.06)	(2.91)	(3.97)	(5.29)	(3.68)
Observations		357	357	357	357	357	357	357	357
R-squared		0.080	0.049	0.056	0.061	0.059	0.055	0.036	0.031

Notes: Robust standard errors in parentheses ***p<0.01, **p<0.05, *p<0.1; IDDS – Individual Dietary Diversity Score

Table 2.8. Association between Women's Dietary Diversity Score (WDDS) and BMI – OLS and QR results for women aged 15 years and above

Variables	Unit	OLS	Quantile Regression						
			5th	10th	25th	50th	75th	90th	95th
WDDS	Count	-0.83*	0.66	0.39	-1.07*	-0.22	-0.30	-2.77**	-3.37***
		(0.42)	(0.70)	(0.84)	(0.58)	(0.35)	(0.53)	(1.32)	(1.05)
Distance	kilometer	-0.17***	0.04	-0.05	-0.17**	-0.06	-0.11	-0.43***	-0.55***
		(0.06)	(0.09)	(0.10)	(0.09)	(0.05)	(0.08)	(0.16)	(0.11)
Distance*WDDS		0.03	-0.02	-0.00	0.03	-0.00	0.01	0.09**	0.14***
		(0.02)	(0.02)	(0.03)	(0.02)	(0.01)	(0.02)	(0.04)	(0.04)
Age	Years	0.24***	0.28***	0.29***	0.28***	0.30***	0.23**	0.10	-0.09
		(0.05)	(0.05)	(0.07)	(0.09)	(0.07)	(0.10)	(0.18)	(0.13)
Age square	Years	-0.00***	-0.00***	-0.00***	-0.00**	-0.00***	-0.00**	-0.00	0.00
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Marital status	Ref: 1. Married								
	2. Unmarried	-0.16	0.52	0.39	0.25	-0.18	-0.91	-2.12**	-2.46**
		(0.55)	(0.76)	(0.87)	(0.92)	(0.67)	(0.58)	(1.04)	(1.20)
	3. Widow/Divorced	0.64	0.36	0.77	0.19	1.32*	0.36	0.35	0.71
		(0.46)	(0.57)	(0.56)	(0.58)	(0.73)	(0.59)	(0.97)	(1.07)
Education	Years	0.02	-0.05	-0.03	0.03	0.02	0.04	0.05	0.02
		(0.03)	(0.05)	(0.06)	(0.04)	(0.03)	(0.03)	(0.07)	(0.07)
Occupation	Ref: 1. Housewife								
	2. Office work	0.10	0.49	0.26	0.08	-0.10	0.16	1.36	0.74
		(0.49)	(0.44)	(0.60)	(0.51)	(0.62)	(0.61)	(1.10)	(0.95)
	3. Labor work	-0.74	-1.13*	-0.85	-0.95**	-0.65	-1.03***	-2.07***	-2.74***
		(0.46)	(0.64)	(0.64)	(0.45)	(0.56)	(0.40)	(0.69)	(0.58)
	3. Others	-0.60	-0.42	-0.04	-0.80	0.05	-0.54	0.95	-0.73
		(0.59)	(0.65)	(0.73)	(0.85)	(0.73)	(0.76)	(1.75)	(1.49)
Children	Count	0.31***	0.04	0.20	0.26**	0.33***	0.37***	0.45*	0.28
		(0.10)	(0.15)	(0.14)	(0.13)	(0.13)	(0.09)	(0.24)	(0.25)
HH size	Count	0.05	0.07	0.04	0.11*	0.12**	0.09*	0.00	0.00
		(0.06)	(0.07)	(0.10)	(0.07)	(0.05)	(0.06)	(0.10)	(0.11)
Religion	1=Hindu	-0.61	0.43	-0.57	-0.26	-0.64	-0.94	-1.78	-1.80*
		(0.80)	(1.86)	(0.58)	(0.58)	(1.30)	(1.16)	(2.09)	(1.02)
Caste	Ref: 1. General								
	2. SC&ST	-0.26	-0.20	-0.12	-0.04	-0.23	0.05	0.04	-1.03
		(0.36)	(0.39)	(0.45)	(0.42)	(0.43)	(0.47)	(0.72)	(0.72)
	3. OBC	0.81**	0.13	0.26	1.27***	1.11***	1.41***	0.79	-0.45
		(0.36)	(0.51)	(0.61)	(0.41)	(0.41)	(0.46)	(0.70)	(0.60)
Economic status	Continuous	0.31***	0.26**	0.24***	0.32***	0.30***	0.26***	0.35***	0.40***
		(0.07)	(0.12)	(0.09)	(0.07)	(0.07)	(0.08)	(0.11)	(0.11)
Agricultural household	1=Yes	-0.65**	-0.44	-0.30	-0.60*	-0.66*	-0.98**	-0.60	-1.56**

		(0.29)	(0.47)	(0.61)	(0.31)	(0.38)	(0.42)	(0.61)	(0.71)
Safe drinking water	1=Yes	-0.12	-0.70	-0.64	-0.78	0.07	0.32	0.84	2.10***
		(0.56)	(0.78)	(0.98)	(0.99)	(0.67)	(0.68)	(0.96)	(0.73)
Sanitation	1=Yes	1.66*	0.25	1.55**	1.39*	2.07	2.04**	-0.19	1.60
		(0.83)	(0.71)	(0.63)	(0.71)	(1.49)	(0.91)	(1.79)	(1.35)
Transect	1=Northern	0.39	-0.61*	0.07	0.39	0.39	0.32	1.22**	0.60
		(0.29)	(0.37)	(0.42)	(0.32)	(0.33)	(0.43)	(0.59)	(0.65)
Constant		18.63***	7.99**	9.42**	15.01***	14.25***	18.94***	35.73***	42.62***
		(2.74)	(3.49)	(4.31)	(4.03)	(2.56)	(3.67)	(8.88)	(5.29)
Observations		1,221	1,221	1,221	1,221	1,221	1,221	1,221	1,221
R-squared		0.157	0.106	0.133	0.152	0.149	0.151	0.122	0.080

Notes: Robust standard errors in parentheses ***p<0.01, **p<0.05, *p<0.1; WDDS – Women's Dietary Diversity Score

2.6. Discussion and Conclusions

We study the association between DD and anthropometric outcomes of children and women in the rural-urban interface of Bangalore. Together with OLS regression, we apply the QR method to cast light on the heterogeneity of this relationship. We use six different measures of individual- and household-level DD which enables us to check the consistency of these results. The study was conducted for three different age groups – younger children (<6 years), older children (6-14 years), and women (15 years and above).

We find that none of the associations between DD and anthropometric outcomes for younger children, older children, and women are significant at the mean, with the exception of two individual-level DD measures (CDDS and individual FVS) that are positively associated with WAZ scores for younger children. The QR results are quite similar to the OLS results. With one exception we do not find any evidence of a consistent association between DD and anthropometric outcomes for younger children. The exception is that increasing DD at the upper end of the WAZ distribution is associated with higher WAZ score, implying an increased prevalence of overweight/obesity. Thus, it seems that the OLS results are driven by the children in the upper quantiles of the WAZ distribution. This result is observed for one of the individual-level measures and two of the household-level measures, highlighting the sensitivity of results to different measures of DD. A similar result is observed for older children at the upper quantile of BMI z-scores distribution. Here as well, we observe a similar sensitivity between the individual- and household-level DD measures. For women, we find no consistent significant association of DD with their BMI.

Several limitations of our study should be noted. We use cross-sectional data, which limits our ability to address possible endogeneity. It does not allow us to account for intra-year seasonal variations in DD and their implications for anthropometric outcomes. Despite these limitations, we can draw several conclusions with confidence:

First, except for the 95th quantile of WAZ of young children and BMI z-scores of older children, there is no evidence of any significant relationship between different DD measures and anthropometric outcomes. Thus, policies focusing on improving DD in this specific setting will not be effective in improving (most) anthropometric outcomes across age and gender cohorts, and may even be counter-productive as discussed below.

Second, we do find that higher DD is associated with higher z-scores in the upper quantiles of the WAZ distribution among young children and in the upper quantiles of the BMI z-scores distribution among older children. This is a worrisome result because children in these quantiles are already over-nourished and a further increase in DD increases the probability of them being overweight/obese. This is contrary to the widely accepted opinion that improved DD is associated with better anthropometric outcomes. One reason for these contradictory results could be that a more diverse diet might be accompanied by a higher intake of fat, sodium, sugar, etc. resulting in excess weight gain. A diet's quality depends not only on the intake of adequate quantities of micronutrients, but also on the balanced intake of energy, saturated fat, sodium, and sugar (Savy et al., 2008). Thus, there is a need to devise DD measures that can account for the negative effect of higher intake of sugar, fat, cholesterol, sodium, etc. especially in areas facing multiple burdens of malnutrition. Furthermore, the sensitivity of our results to the choice of DD measure implies that relying on just one measure of DD may be inadequate. Measures such as FCS, FVS, and DDS use similar data but differ in the depth of information they provide about dietary quality. Thus, using several complementary DD measures might provide more robust results and improve our understanding of the relationship between DD and anthropometric outcomes.

Third, some studies conduct disaggregated analysis for rural and urban areas and find significant associations of DD with anthropometric outcomes either in rural (Amugsi et al., 2014) or urban areas (Hatløy et al., 2000). However, in our sample, with the sole exception of WAZ at the 95th quantile among younger children, whether a household is located in a more urban or rural setting has no significant effects on the relationship between DD and anthropometric outcomes. Since a large proportion of the population in India (and elsewhere) lives in rural-urban interfaces such as the one that we study, our results confirm that there is a need to go beyond simple rural-urban dichotomies in the analysis of urbanization, diets, and health.

Finally, our results confirm that examining the relationship between DD and anthropometric outcomes at the mean (using the OLS method) can obscure variations in this relationship across different subsets of the population. Hence, it is important to study the relationship over the entire distribution using methods such as QR.

2.6.1. Policy implications

The results of our study reveal no strong and monotonic relationship between DD and anthropometric outcomes. Indeed, for some individuals (e.g. young children with high WAZ scores and older children with high BMI z-scores) we find that increasing DD is associated with unhealthy outcomes. Thus, we are not able to conclude that increasing DD would improve anthropometric outcomes in our study setting. The rapid urbanization in many low- and middle-income countries has led to horizontal growth of cities extending their formal boundaries (Ellis and Roberts, 2015), creating areas similar to the one we study. In such settings, a universal health policy of increasing DD might not be effective in improving anthropometric outcomes.

The global nutrition monitoring framework includes DD as one of the indicators to measure its six global nutrition targets that are to be achieved by 2025 (WHO, 2017). However, many countries face multiple burdens of malnutrition and there is no universal evidence of higher DD leading to reduced malnutrition. As mentioned above and also highlighted by Miller et al. (2020), there are major gaps in the validity of several dietary quality metrics in assessing multiple burdens of malnutrition. This suggests that DD, especially the indices used currently, might not be an effective indicator for assessing progress in nutrition outcomes in all settings. Hence, care is called for when designing policy measures that include DD as an improvement target indicator to measure improvements in health.

Of course, anthropometric outcomes are determined by several factors and complex interactions among them. According to some studies for India (Corsi et al., 2016; Kim et al., 2017), DD is not the most important risk factor associated with undernutrition, and our results support these findings. Factors such as mother's height and household economic status appear to be more important. This suggests the need for a more comprehensive health policy accounting for multiple health inputs rather than focusing on any single aspect.

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Appendix

Appendix 2.1. Logistic regression results for sample selection – Younger children

Variables	Unit	WAZ z-scores	HAZ z-scores	WHZ z-scores
Age	Months	-0.01	0.04***	0.02
		(0.02)	(0.01)	(0.02)
Gender	1=Male	0.28	0.16	0.12
		(0.60)	(0.41)	(0.47)
Mother's age	Years	-0.15***	-0.08**	-0.08*
		(0.05)	(0.04)	(0.04)
Mother's education	Years	-0.25***	-0.13*	-0.11
		(0.09)	(0.08)	(0.08)
Mother's occupation	1=Working	-0.30	1.01*	1.58**
		(0.87)	(0.61)	(0.72)
Mother's additional occupation	1=Yes	-0.65	0.62	-0.10
		(1.09)	(0.80)	(1.17)
Decisionmaker age	Years	-0.02	-0.00	-0.03*
		(0.03)	(0.02)	(0.02)
Decisionmaker gender	1=Male	0.27	-0.65	-0.35
		(0.82)	(0.58)	(0.67)
HH size	Count	-0.03	0.04	0.28*
		(0.23)	(0.10)	(0.16)
Caste	1=General	-1.09	0.04	0.23
		(0.82)	(0.47)	(0.63)
Economic status	Continuous	0.09	0.02	-0.05
		(0.11)	(0.10)	(0.10)
Additional income for the household	1=Yes	0.72	0.63	0.22
		(1.00)	(0.53)	(0.72)
Agricultural household	1=Yes	0.71	-0.84	-0.77
		(0.85)	(0.64)	(0.78)
Off-farm employment	1=Yes	-0.07	0.00	-0.62
		(0.91)	(0.54)	(0.62)
Vegetarian family	1=Yes	-0.82	-0.30	0.32
		(0.86)	(0.70)	(0.72)
Ration card	1=Yes	-0.18	0.44	0.24
		(0.42)	(0.35)	(0.38)
Own house	1=Yes	-1.29	0.90	0.58
		(1.00)	(0.80)	(0.90)
Safe drinking water	1=Yes	1.92**	0.04	0.91
		(0.93)	(0.87)	(0.86)
Distance	Kilometer	-0.00	0.03	0.02
		(0.04)	(0.03)	(0.03)

Transect	1=Northern	-1.13	-0.93**	-1.70***
		(0.71)	(0.44)	(0.56)
Constant		11.65***	0.68	3.38
		(3.56)	(2.82)	(3.66)
Observations		240	240	240

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

Appendix 2.2. Logistic regression results for sample selection –Older children

Variables	Unit	BMI z-scores
Age	Months	0.00
		(0.01)
Gender	1=Male	-0.10
		(0.34)
Mother's age	Years	-0.01
		(0.03)
Mother's education	Years	-0.00
		(0.06)
Mother's occupation	1=Working	0.80
		(0.50)
Mother's additional occupation	1=Yes	0.75
		(0.46)
Decisionmaker age	Years	0.01
		(0.02)
Decisionmaker gender	1=Male	0.03
		(0.46)
HH size	Count	-0.01
		(0.12)
Caste	1=General	-0.50
		(0.48)
Economic status	Continuous	0.01
		(0.12)
Additional income for the household	1=Yes	-0.14
		(0.47)
Agricultural household	1=Yes	0.19
		(0.56)
Off-farm employment	1=Yes	-0.29
		(0.64)
Vegetarian family	1=Yes	1.42
		(1.07)
Ration card	1=Yes	0.09
		(0.39)
Own house	1=Yes	-1.01
		(0.73)
Safe drinking water	1=Yes	0.22
		(0.72)
Distance	Kilometer	0.01
		(0.03)
Transect	1=Northern	-0.40
		(0.50)

Constant	0.82
	(2.52)
Observations	419

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

Appendix 2.3. Logistic regression results for sample selection – Women aged 15 years and above

Variable	Unit	BMI
Age	Years	-0.02*** (0.01)
Education	Years	-0.07*** (0.02)
Occupation	Ref: 1. Others	
	2. Housewife	1.19*** (0.13)
	3. Office work	0.14 (0.20)
	4. Labor work	0.61*** (0.19)
Additional occupation	1=Yes	-0.49** (0.19)
Decisionmaker age	Years	-0.00 (0.01)
Decisionmaker gender	Male	-0.26 (0.16)
HH size	Count	-0.11*** (0.04)
The person doing the grocery shopping	Ref: 1. Others	
	2. Adult female	0.11 (0.20)
	3. Adult male	0.23 (0.16)
Religion	1=Hindu	-0.21 (0.35)
Caste	1=General	-0.08 (0.13)
Economic status	Continuous	0.01 (0.03)
Additional income	1=Yes	0.35*** (0.13)
Ration card	1=Yes	0.02 (0.13)
Own house	1=Yes	0.04 (0.25)
Agricultural household	1=Yes	0.05 (0.16)
Off-farm employment	1=Yes	0.07 (0.15)
Vegetarian family	1=Yes	0.02 (0.24)
Safe drinking water	1=Yes	0.28 (0.22)
Distance	Kilometer	-0.02*** (0.01)
Transect	1=Northern	-0.00 (0.13)
Constant		3.44*** (0.74)
Observations		1,725

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

Appendix 2.4. Summary statistics – Socioeconomic characteristics of sample households

Variable	Unit	Younger children	Older children	Women
Age	Years	3 (1.4)	9.8 (2.6)	38 (15)
Gender	1=Male	54	48	
Mother's height	Centimeter	153 (13)	152 (11)	
Mother's age	Years	26 (4.2)	31 (5.3)	
Mother's /Women education	Years	9.9 (3.7)	8 (3.8)	6.5 (5.2)
Mother's occupation†	1=Working	11	22	
Women occupation†	1=Housewife			70
	2=Office work[(a)]			10
	3=Labor work[(b)]			13
	4=Others[(c)]			7
Number of children	Count			2 (1.6)
Women marital status†	1=Married			80
	2=Unmarried			12
	3=Widow/Divorced			8
HH size	Count	6 (2.4)	5.7 (2.5)	5 (2.4)
Economic status[(d)]	Continuous	9.1 (2.4)	8.7 (2.3)	8.6 (2.5)
Distance to Bangalore city	Kilometer	23 (10)	25 (10)	26 (10)
Caste†	1=General	51	46	47
	2=SC&ST	26	28	27
	3=OBC	23	26	26
Sanitation†	1=Yes	94	96	96
Safe drinking water†	1=Yes	93	94	93
Religion†	1=Hindu	92	93	94
Vegetarian family†	1=Yes	10	10	9
Own house†	1=Yes	70	77	86
Agricultural household[(e)]†	1=Yes	50	60	63
Primary decision maker gender†	1=Male	78	81	74
Transect†	1=Northern	51	52	50

Notes: † indicates variable values expressed in percentages; Standard deviations in parentheses.

[(a)] Office work includes income-earning activities in public and/or private sector, managing own off-farm business activities, and off-farm subcontracting

[(b)] Labor work includes work on own farm and permanent and casual labor on others farm.

[(c)] Other types of occupation include those women who are still students, unemployed, and unable to work.

[(d)] The asset index is considered as a proxy for the economic status of the household. It is constructed based on the new socio-economic classification system developed by the Market Research Society of India. This classification system is based on two variables such as the education of the household primary decision-maker and the number of consumer durables owned by the household.

[(e)] Agricultural households are those which produce at least one crop or livestock product in the year 2016.

3. Processed food consumption and peri-urban obesity in India

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Abstract

In 2015-16, India was the seventh-largest economy in the world and had more than 200 million people at risk for obesity. Overconsumption of calories from processed foods, an outcome of a country's dietary transition, is known to be an important mechanism that drives risks for obesity. Testing the nature of this relationship in India has not been possible thus far due to the limited availability of relevant data. In this paper, we use novel cross-sectional data from a primary socio-economic survey conducted in the rural-urban interface of Bangalore, a mega-city in India, to explore the role of dietary transition in rising obesity. We model how calories from semi- and ultra-processed foods are associated with the prevalence of obesity (Body Mass Index (BMI) ≥25) among women. We find that excess consumption of calories from semi-processed foods is positively associated with obesity. Especially, the households with lower socioeconomic status are at higher risk of obesity due to excess consumption of calories from semi-processed foods. However, there is a shift in the diet correlates of obesity towards ultra-processed foods for households with higher socioeconomic status. The results also suggest that there might be a threshold only after which calories from processed food consumption and obesity prevalence become inter-connected. In line with this, we find that excess consumption of semi-processed food calories is strongly associated with an increase in obesity among women who meet their recommended dietary allowance (RDA) for calories. Furthermore, labor-intensive physical activities seem to alleviate the effect of overconsumption of semi-processed foods on obesity. The findings of our study highlight the increasing risks for diet-related nutrition problems at a relatively lower level of dietary transition. This calls for designing strategic interventions about the consumption of semi-processed foods to control the increasing prevalence of obesity in India.

Keywords: Obesity, dietary transition, structural transformation, rural-urban interface, urbanization, India.

3.1. Introduction

Transition in the food consumption patterns towards energy-dense, fatty, salty foods and sweetened beverages is one of the widely attributed factors for the shift in the nutritional problems from undernutrition to overnutrition, especially in low- and middle-income countries (LMICs) (Popkin et al., 2012; Popkin, 2009, 2001; Shetty, 2002). Transformations in the global food systems from fresh markets to modern retail chains have increased the ease of access to processed and packaged foods and beverages (Pingali, 2007; Popkin, 2017, 2014; Reardon et al., 2003; Zhou et al., 2015). Furthermore, rising off-farm wages have increased the opportunity cost of preparing food at home leading to higher consumption of processed foods and frequent dining out practices (Kennedy and Reardon, 1994; Regmi and Dyck, 2001). Processed foods are the outcomes of different levels of industrial processing. Many industrial production processes make them highly palatable and less satiating, which eventually leads to their overconsumption (Fardet, 2016; Monteiro et al., 2013). Combined with the reduction in physical activity due to the changing work-effort during structural transformation (ST),[7] excess calories from overconsumption increases body fat and hence the BMI (Hill et al., 2012). This increase in body weight often leads to greater obesity and incidence of non-communicable diseases (NCDs) in otherwise nutrition insecure populations (Ford et al., 2017; Popkin et al., 2012; Popkin, 2006).

In India, there has been a rapid increase in the prevalence of obesity in the last decade (NFHS-5, 2019-20). Aiyar et al. (2021) show that much of this increase can be attributed to the spillover effect of ST from the nearby urban centers. Dang et al. (2019) find that changing work effort due to occupation transitions towards less physically demanding activities is correlated with obesity. However, due to the lack of detailed dietary data, these authors also acknowledge that they cannot explore the role of the dietary transition in the prevalence of obesity. Other papers such as Meenakshi (2016), Subramanian et al. (2009), and Subramanian et al. (2011) show that the income-obesity gradient has been tilting away from the higher socio-economic status group but, they too, do not explore the role played by diets.

In this paper, we estimate the association between processed food consumption and obesity in fast-growing peri-urban areas. The dietary patterns of urban people are distinctly different from their rural counterparts especially in the consumption of processed foods (Bren d'Amour et al., 2020; Cockx et al., 2018; Popkin, 2001). In India, fast-paced urbanization, improved infrastructure, and the emergence

[7] ST reallocates the workforce and economic output share from labor-intensive (e.g. agriculture) to capital-intensive (e.g. industry and service) activities (Herrendorf et al. 2014). Such a change in occupational patterns reduces the energy expended in work (Monda et al. (2008)). Along with these changes in work-effort in the labor force, ST comes to be associated with greater urbanization and greater dietary diversity (Rahman and Mishra (2020)). The latter is also associated with an increase in access to processed food items and an increase in risk for obesity (Pingali and Khwaja (2004); Popkin (2001); Popkin et al. (2012); Shetty (2013)).

of small towns have blurred the boundaries between rural and urban areas, leading to the creation of complex rural-urban interfaces (Denis et al., 2012; Pingali et al., 2019). Facilitated by access to economic opportunities and a higher opportunity cost of time spent on cooking food at home, there is a growing demand for processed foods among urban consumers (Bairagi et al., 2020; Drewnowski and Popkin, 1997; Rao et al., 2006). The diverse food markets in urban areas cater to such increased demand (Demmler et al., 2018; Reardon et al., 2003). Thus, analyzing the peri-urban experiences provides an opportunity to measure how ST in these peri-urban areas affects obesity through a dietary transition to greater consumption of processed foods. To this end, we utilize a unique cross-sectional primary survey that collected socio-economic, diet, and nutrition-related information of women living in the rural-urban interface of the mega-city of Bangalore (India). Using the NOVA classification system (Monteiro, 2009), we model how different levels of industrial processing of foods consumed affect the prevalence of obesity in the rural-urban interface.

We make three contributions to the literature. First, accounting for different levels of food processing is important to understand the diet correlates of obesity. Literature, mainly from high-income countries, shows that the excess consumption of ultra-processed foods such as sweetened beverages, ready-to-eat meals, and fast-foods increases obesity (Asfaw, 2011; Monteiro et al., 2018; Poti et al., 2017). Studies for LMICs show that increased intake of calorie sweeteners, edible oil, and animal food is associated with obesity prevalence (Misra et al., 2011; Popkin et al., 2012; Popkin, 2009; Popkin and Gordon-Larsen, 2004; Shetty, 2002). In India too, the consumption of ultra-processed foods such as sweetened beverages and processed snacks is on the rise. In our study, we use the NOVA classification to disentangle the effects of calories consumed from semi-processed foods as opposed to ultra-processed foods on obesity. We show that consumption of semi-processed foods matters more than the ultra-processed foods for obesity prevalence, especially among lower-income groups. At higher income levels, the relationship between ultra-processed food and obesity becomes evident. This suggests that obesity growth in peri-urban areas, which are in the middle of their ST, first becomes linked with the consumption of semi-processed foods. Hence, identifying household drivers for consumption of these semi-processed foods may provide key clues for controlling the obesity epidemic reaching lower-income groups in LMICs. We provide some exploratory evidence that ration card holders, who procure subsidized semi-processed foods, are at greater risk from this dietary relationship with obesity. This suggests that there is a need for the reform of how food is distributed through the urban public distribution system (PDS).

Second, many countries provide RDA guidelines for individuals to lead a healthy life. Most countries do not account for the role of processed foods in contributing calories to meet these RDAs.[8] For example, if an individual's calorie consumption is lower than his/her RDA, consumption of processed calories could result in weight gain. But this would reduce extreme thinness (BMI<18.5) without affecting risks for obesity. On the other extreme, for an individual consuming more calories than his/her RDA, overconsumption of processed calories will increase the propensity for obesity. Thus, when studying the role of processed foods, we propose that it is important to distinguish obesity risks based on an individual's baseline ability to meet their specific RDA. We provide some evidence that the effect of processed food calories on obesity is stronger for individuals who consume more calories than their RDA. This indicates that there is a threshold effect in the relationship between processed food consumption and obesity during the ST process which may also be driven by overconsumption.

Finally, it is well known that more physical activity is crucial to reduce the risk of obesity caused by excess calorie consumption (Dang et al., 2019; Monda et al., 2008; Popkin, 2009). We add supporting evidence that the effects of excess consumption of semi-processed foods on obesity prevalence can be somewhat alleviated by greater physical activity. Obesity in women engaged in relatively labor-intensive physical activities exhibits a weaker relationship with the consumption of semi-processed food.

The rest of the paper is structured as follows. We discuss the recent trends in the diet transition and obesity in India in section. 3.2. Then, in section 3.3, we discuss our study area and sampling technique, and describe the data and elaborate on the sample characteristics. Section 3.4 explains the empirical method employed and section 3.5 discusses the results. Lastly, we summarize our findings and draw conclusions in section 6.

3.2. Background

3.2.1. Changing diets and the role of processed foods in India

Pingali and Khwaja (2004) identify two distinct stages in dietary transition associated with ST in India. The first stage marks the income-induced shift from the consumption of a few traditional cereals such as rice and wheat towards a diversified diet, leading to improved diet quality. In the second stage, the influence of urbanization and globalization results in the excess consumption of sugar, oil, sweetened beverages, fast and convenient foods. Excess consumption of such food items, as discussed before, is associated with an increase in the prevalence of obesity.

[8] There are three exceptions - Brazil (Brazilian Ministry of Health 2015); Ecuador (Ministerio de Salud Publica del Ecuador 2018); Peru (Ministerio de Salud del Perú 2018); Uruguay (Ministerio de Salud del Uruguay 2016).

Studies on urban diets in India have identified changing dietary patterns towards processed foods. Daniel et al. (2011) find that dietary patterns in two large cities in India, Mumbai (West India) and Trivandrum (South India), are characterized by excess consumption of fried snacks and sweets. Satija et al. (2015) show that two of the three dietary patterns among factory workers in India are associated with a higher intake of snacks. Rathi et al. (2017) find that during a 24-hour dietary recall, at least half of adolescents living in a city in India—Kolkata—consume three or more servings of energy-dense snacks and beverages. Using large longitudinal data on purchased consumer goods, Law et al. (2019) find an increasing trend in the purchase of sweet and salty snacks, edible oils, and other processed foods among urban households. Among these dietary patterns, the ones that are rich in sugar, salt, oil, and animal food are found to be positively associated with the incidence of obesity (Daniel et al., 2011; Green et al., 2016; Satija et al., 2015).

However, it is not clear from these studies whether obesity results from the excess consumption of semi-processed foods like sugar, salt, oil, and animal food, or whether it is caused by the excess consumption of ultra-processed foods. Why should this matter? First, semi-processed foods are likely to be consumed in greater quantity in a diet at lower income levels since they may be more affordable. In India sugar is made available at a relatively stable and low price by the PDS while sweetened beverages are available through the market. Thus, among lower-income groups, increased income associated with urban growth may enable individuals to purchase and consume more semi-processed foods such as sugar (than ultra-processed sweetened beverages). Hence, even though ultra-processed foods may be more calorie-dense and satiating than semi-processed foods, if semi-processed foods account for a larger share of an individual’s consumption, they will make a correspondingly larger contribution to his/her risk of obesity. Second, there may be a high opportunity cost of time associated with cooking among higher-income groups. Hence, they may prefer to consume ultra-processed foods to save time. At lower or moderate-income levels, however, this opportunity cost of time may not be as high. Thus, individuals in the lower-income group may choose to consume more semi-processed foods relative to ultra-processed foods. This could also explain why obesity-enhancing effects of semi-processed foods may be stronger than the effects of ultra-processed foods at lower-income levels. In this paper, we account for such differences in the level of food processing while estimating the relationship between processed food and obesity.

3.2.2. Obesity in India's rural-urban interface

Indian urbanization is distinct from other countries in two ways. First, the emergence of the fast-growing small towns has been the major driver of urban population growth in the recent decade (Denis et al., 2012). These small towns further fuel the living standards and nutritional outcomes of people in nearby rural areas (Aiyar et al., 2021; Gibson et al., 2017; Rao et al., 2006). Second, India’s urbanization patterns can be represented by polycentric patterns. That is, the urban effects extend from the big city to surrounding small towns which then spill over into the rural areas (Steinhübel and Cramon-Taubadel, 2020). In the rural-urban interface, it is common to see households diversify their livelihood strategies to the off-farm sector even while at least one member is still engaged on the farm (Steinhübel and Cramon-Taubadel, 2020). The resulting increased income from livelihood diversification allows for the simultaneous diversification of diet, and an increased frequency of eating out (Pingali, 2007; Rahman and Mishra, 2020).

Pingali and Khwaja (2004) propose that the speed of shift from the first stage to the second stage of diet transition depends on the speed of urbanization of the location. An urban environment allows for both access and affordability of diverse foods. Furthermore, the urbanization spill-over effects in such region, catalyzed by access to better infrastructure and transportation facilities, reduce engagement in labor-intensive activities as the lifestyle becomes more sedentary. In combination with the increased calorie intake through dietary transition, reduced physical activities create an imbalance between calorie consumption and expenditure. This increases the prevalence of obesity obese in rural-interface regions.

The spillover effects of ST from the nearby urban centers provide easy access to processed foods, sedentary activities, and lifestyle changes. Hence, people living in this rural-urban interface are likely to be at a higher risk for obesity than their counterparts living in rural areas (Aiyar et al., 2021). Our study, thus, provides descriptive evidence on how dietary transition to processed foods leads to greater obesity in the face of rapid urbanization in the rural-urban interface of Bangalore.

3.2.3. Bangalore

With a population of 9.6 million (Directorate of Census Operations Karnataka, 2011), Bangalore is a rapidly urbanizing megacity situated in the southern state of Karnataka. It is expected that Bangalore's population will rise to 20.3 million by 2031 (Bharadwaj, 2017). Bangalore along with several small towns located within a roughly 40-kilometer radius provides many opportunities for engaging in intensive agriculture and employment in the off-farm sector (Directorate of Census Operations Karnataka, 2011; Steinhübel and Cramon-Taubadel, 2020). Several highways connecting these urban centers have led to a rise in urbanization in the entire region (Directorate of Census Operations Karnataka, 2011). Bangalore exerts a rapidly growing demand for diverse food items from nearby peri-urban and rural areas and serves as a central hub from where the food is distributed. During the time data was gathered, the obesity rate among women in Bangalore increased from 32 percent (2015-16) to 40.1 percent (2019-20) (NFHS-5, 2019-20). Several modern retail stores and fast-food centers have emerged in Bangalore during the same time. The rapid rise in access to food markets reflects the growing demand for convenience and processed foods (Demmler et al., 2018). Besides, the

Government of Karnataka provides subsidized ration for semi-processed foods such as oil, sugar, etc. for disadvantaged families at relatively low prices (Government of Karnataka, 2013).[9]

3.3. Study area, sampling, and data description

3.3.1. Study area and sampling design

Our study area, set in the rural-urban interface of Bangalore, consists of two research transects (see Fig. 3.1). The first transect extends outwards and towards the North and the second extends towards the southwest part (two polygons in Fig. 3.1). These transects are surrounded by several small towns. Improved access to Bangalore city and the small towns offers incentives for households to engage in commercialized agricultural operations and off-farm employment across this region (Steinhübel and Cramon-Taubadel, 2020). Thus, the livelihood strategies of the households located in the rural-urban interface region are mostly a composite of farm and off-farm employment. Such diversifications in livelihood strategies of the households increase their average income (Haggblade et al., 2010). Increased income enables the households to purchase food items from a wide range of food outlets, from mom & pop stores to hypermarkets existing in the region. All these stores sell food ranging from fresh to semi-processed to ultra-processed foods. A variety of fast-food outlets also exist within these transects and in surrounding small towns, creating easier access to semi- and ultra-processed food items. Furthermore, improvements in infrastructure, transport facilities, access to off-farm employment in this region have made a more sedentary lifestyle possible for many local inhabitants. Hence, the rural-urban interface of Bangalore, a space influenced by urbanization, globalized diet, sedentary activities, and lifestyle changes, provides an ideal setting to explore how calories from processed foods translate into obesity.

For our empirical analysis, we use the data from a socio-economic survey of 1275 households conducted between December 2016 and May 2017 in the rural-urban interface of Bangalore. We applied a two-stage stratified random sampling method to ensure that the sample households represent the urbanization pattern in this area. In the first stage, all the villages in each transect were divided into three strata (urban, peri-urban, and rural) using the "Survey Stratification Index (SSI)" (Hoffmann et

[9] The Government of Karnataka categorizes households as priority and non-priority households based on certain eligibility criteria to define the economic status of the household (Government of Karnataka 2013). Priority households hold Anthyodaya Anna Yojana (AAY) card or Below Poverty Line (BPL) card. In addition to subsidized staples such as rice and wheat, the households with AAY and BPL cards are entitled to receive sugar, oil, gram, and other region-specific food items (Government of Karnataka 2013). Non-priority households, who do not meet the criteria of living in poverty, are not eligible for subsidized food under PDS. However, if they feel that they are food insecure, they can register for an Above Poverty Line (APL) card to receive a small quantity of subsidized grains such as rice.

al., 2017). Then, in each of these strata, sample villages were randomly selected proportional to their size (in total 61 villages). In the second stage, households were randomly selected in each village again proportional to their size using village household list maintained by the publicly run village kinder gardens.

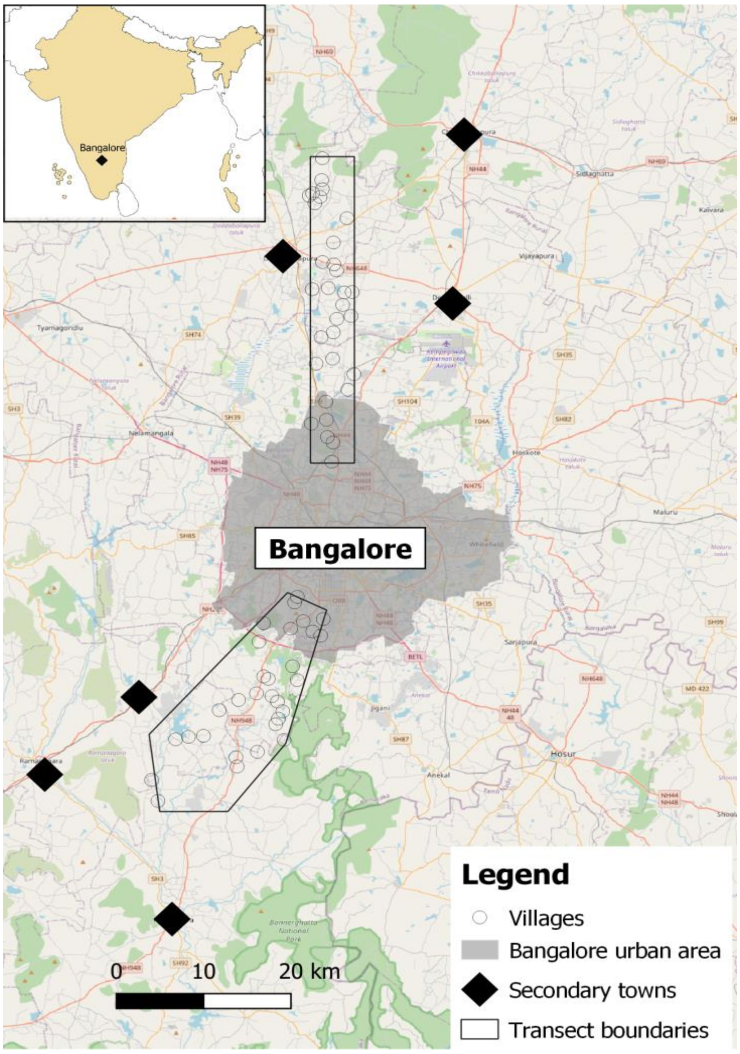

Figure 4.1: Study area, research transects, and sample villages.

Information on socioeconomic, demographic, livelihood characteristics, etc. of sample households was collected using a comprehensive questionnaire. The caregiver of the family was interviewed to collect the information on household food consumption up to 14-days before the interview.[10] Anthropometric measurements such as height and weight were taken for all the women living in these sample households, except for pregnant and nursing women. We concentrate on obesity among women

[10] The survey instrument for the 14-day recall household food consumption data was prepared based on the Food and Agricultural Organization (FAO) guidelines for household food consumption expenditure survey in low- and middle-income countries.

because women are disproportionately affected by obesity in India (NFHS-5, 2019-20). Besides, women are usually the main caregivers in Indian society. Increased opportunities for them to work outside the home have implications not just for their own health but also for the care they can provide to the family (Kennedy and Reardon, 1994; Regmi and Dyck, 2001). Additionally, the nutrition of women is found to be directly correlated with the nutritional status of other members within the household (Harttgen et al., 2013).

3.3.2. Data description

3.3.2.1. Survey overview

While our survey consists of 1275 households, demographic and food consumption data were available for only 1121 households. Of these, we had to drop 22 households owing to extreme calorie consumption values which we consider to be outliers.[11] Hence, our sample consists of 1099 households. A total of 1983 women were recorded as members of these households. Even after multiple visits to households, we could only collect anthropometric measurements for 1438 women. Hence, anthropometric data is not available for 29% of the women in our sample. The t-test results presented in Appendix 3.1 show that there are differences in some of the individual-level (marital status and occupation) and household-level characteristics (family size, asset index, and distance to Bangalore city) of women who did/did not participate in anthropometric measurements. Participated women on average are more likely to be housewives and married. They are more likely to be from households with fewer members, higher wealth, and are located closer to Bangalore city. Controlling for these factors reduces the sample by 68 observations due to missing covariates. Results of the t-tests summarized in Appendix 3.2 suggest that there is no significant difference in BMI of women for whom a covariate is missing or not missing. Our final sample consists of 1335 women for whom complete information on BMI, processed food consumption, and covariates are available. In Table 3.1, we present the summary statistics of the final data set.

Table 3.1: Summary statistics of the sample women and households

Variable	Unit	Mean	Median
Dependent variable			
BMI	Kg/m2	23 (4.9)	23
Obesity†	BMI≥25 Kg/m2	36	
Main explanatory variable			
Share of calories in NOVA food group	Unprocessed and minimally processed foods (%)	74.4 (9.3)	75.1
	Semi-processed food (%)	17.8 (7.5)	17
	Ultra-processed food (%)	4.1 (4.0)	3.2
Controls:			

[11] The observations in the 1st percentile (<=979 Kcal/AE/day) and 99th percentile (>=11379 Kcal/AE/day) are considered as extreme calorie values.

Individual-level characteristics			
Age	Years	38 (14.7)	35
Marital status†	1. Married	80	
	2. Unmarried	12	
	3.Divorced/widowed	8	
Literacy†	Dummy variable; 1. No education	37	
Main occupation†	1. Housewife	69	
	2. Office work	10	
	3. Labor intensive work	13	
	4. Student	7	
Number of children	Numer of children a woman has	2 (1.5)	2
Household-level characteristics			
Family size	Count of household members	5.1 (2.4)	5
Caste†	1. General	45	
	2. SC&ST	27	
	3. OBC	28	
Economic status	Count of durable assets owned by the household	5.9 (1.5)	6
Food source	Market purchase from modern food outlets (%)	22.4 (28.3)	5.8
Person buying food†	1. Adult female	26	
	2. Adult male	57	
	3. Anybody in the family	17	
Livelihood strategy†	1. Pure farm	22	
	2. Pure off-farm	47	
	3. Composite (farm and off-farm)	28	
	4. Others	3	
Ration card†	1. APL	7	
	2. BPL	82	
	3. No ration card	11	
Toilet†	Dummy variable; 1. Yes	82	
Calorie adequacy ratio†	1. Individuals in calorie adequate households	71	
	2. Individuals in calorie inadequate households	29	
Location characteristics			
Distance to Bangalore	Kilometer distance from village centers to Banglaore city center	25.4 (10)	23
Distance to the closest town	Kilometer distance from village centers to the nearest small town	11.5 (3)	11
Transect†	Dummy variable; 1. South	49	
Observations	1335		

Note: † indicates variable values expressed in percentages, standard deviations in parenthesis

[(a)] Livelihood strategy of the household is calculated using the occupation information of all adult household members (>15 years of age). Farm household includes all household members engaged in farm activities; Off-farm household includes all household members engaged in non-farm activities; Farm and off-farm household include a composite of farm and non-farm activities done by household members; The fourth category – Others – includes those households solely engage in dairy farming or does not engage in any livelihood strategy.

3.3.2.2.Dependent variable

We use anthropometric measurements to calculate the BMI of women. BMI is calculated by dividing the weight (in kilograms) of an individual by the square of their height (in meters). Women with BMI≥25 are considered obese. We have 36 percent of obesity (Table 3.1) among our sample women in the rural-urban interface of Bangalore.

3.3.2.3. Independent variable

Our main variable of interest is the calories consumed from processed foods. For this, we need a reliable measure to identify the distinctions between unprocessed, semi-processed, and ultra-processed food items. Moubarac et al. (2014) review five different processed food classification systems from different parts of the world. They suggest that the NOVA food classification system, which accounts for different levels of industrial processing, is consistent and can be used globally in designing dietary guidelines. The NOVA food classification system is widely used in the literature to study the relationship between processed food consumption and health (Juul et al., 2018; Monteiro et al., 2011; Moubarac et al., 2013). Furthermore, its approach to identifying ultra-processed food products in diets is highly recognized in the literature (Lawrence and Baker, 2019). Since we hypothesize that the level of food processing plays important role in predicting obesity, we adopt the NOVA classification system. This system classifies food items into three groups according to the *"nature, extent, and purpose"* of industrial processing (Monteiro, 2009). Information on processing includes the physical, chemical, and biological treatments that food items undergo after separating them from their natural form and before they are consumed as dishes or ingredients. The three food groups of the NOVA classification system are (i) Unprocessed and minimally processed foods, (ii) Processed culinary or food industry ingredients, and (iii) Ultra-processed foods. A detailed description of these three food groups is given in Monteiro et al. (2010).[12]

We calculate calories consumed in each of the NOVA food groups using the 14-day recall household food consumption data provided by the caregiver. The reported quantities of all food items consumed are converted to their caloric values using nutrient conversion factors provided in the Indian Food Conversion Tables (IFCT) (Longvah et al., 2017). The calorie values of each food item are added together to get the total amount of calories consumed by household j, i.e., cal_j. We categorize all the food items, their quantities, and respective calories into 3 groups (k) of the NOVA classification system – unprocessed or minimally processed (m), processed culinary or food industry ingredients (c), and ultra-processed food products (u). The calories within each group k are added together to get

[12] In Appendix 3.3 we summarize all the food items consumed by our sample households into the 3 food groups of the NOVA classification system.

the calories consumed in each NOVA food group for household j, i.e., $q_{k,j}$. The share of calories consumed by group k for household j, is computed by dividing the calories consumed in group k ($q_{k,j}$) by the total amount of calories consumed (cal_j).

$$Kcal_{k,j} = \frac{Amount\ of\ calories\ consumed\ in\ group\ k\ by\ household\ j}{Total\ amount\ of\ calories\ consumed\ by\ household\ j} * 100 = \frac{q_{k,j}}{cal_j}$$

Where $k = (m, c, u)$

We also calculate the quartiles for each type of food group using $Kcal_{k,j}$. Since we are interested in estimating the effect of processed foods on obesity, we consider the calories from the last two processed food groups of the NOVA classification system – $Kcal_{c,j}$ and $Kcal_{u,j}$. For the convenience of interpretation, we call them semi- and ultra-processed foods, respectively.[13]

In Table 3.1, we can see that three fourth of calories in household diets (75 percent) come from unprocessed or minimally processed food groups. The two processed food groups—semi- and ultra-processed foods—account for around 18 and 4 percent of the total calories consumed, respectively.

3.3.2.4. Calorie adequacy ratio

To estimate the relationship between processed food calories and obesity among women whose calorie consumption meet or do not meet their RDA, we calculated the adequacy of the calories consumed by the households. Based on Standardized calorie intake recommendations given by the Indian Council of Medical Research (ICMR), the adequacy of a household's calorie consumption is estimated in three steps. First, the age and gender information of all family members was used to calculate the recommended quantities of calories to be consumed by the household. Second, the total quantity of calories consumed by the household was calculated using 14-day recall food consumption data in the same way as described above. Third, the total quantity of calories consumed by the household was divided by the total calories recommended for the same to produce a calorie adequacy ratio. Households for which the calorie adequacy ratio is greater (less) than one are considered as calorie adequate (inadequate) households. In our sample, 71 percent of the households are calorie adequate and 29 percent are calorie adequate (Table 3.1).

[13] We do not estimate the effect of calories from unprocessed or minimally processed ($Kcal_{m,j}$) group on obesity. This classification contains food items with no or minimum level of food processing to increase their shelf life and palatability; they often do not lead to obesity.

3.3.2.5. Control variables

Besides the semi- and ultra-processed food calories, we also control for the individual- and household-level characteristics of women in our estimations. Among the individual-level characteristics of women (Table 3.1), the average age is 38 years, 37 percent have no education, the average number of children is two, and 80 percent are married. 69 percent of our sample women report being housewives, 10 percent engages in relatively sedentary work in the public or private sector, 13 percent do labor-intensive activities such as agriculture and casual labor, and the remaining 7 percent are students.

Among the household-level controls summarized in Table 3.1, we see that sample households have around five members. The variables related to caste control for the influences of social status and economic opportunities. In our survey 45 percent of women belong to the General caste, 27 percent belong to scheduled caste and scheduled tribe (SC&ST), and 28 percent belong to the other backward castes (OBC) group. We include the number of durable assets owned by the household as a measure of economic status. The majority (48 percent) of our sample households engage in pure off-farm employment, 22 percent engage in pure farm operations, 28 percent are composite households doing both farm and off-farm employment, and the remaining 3 percent either engage in only livestock production or do not engage in any employment.

We also control for the factors that are directly related to household food consumption such as the food source and the person buying food from the market (Table 3.1). On average 22 percent of purchased food in our sample household comes from modern supermarkets. In 26 percent of our sample households, the market food purchases are carried out by a female household member. It's an adult male household member in 57 percent of sample households who does food purchases and in the remaining 17 percent, any member of the household may buy food from the market. 82 percent of our sample households have access to private toilets. In addition, we control for the distance to Bangalore city and closest town to control the effect of proximity to the urban center.

3.4. Methods

Using a probit model we estimate the effect of semi- and ultra-processed food calorie consumption on obesity.[14] The equation below summarizes our econometric model that estimates the relationship between processed calorie consumption and obesity conditional on household- and individual-level characteristics.

$$Y_{i,j} = \beta_0 + \alpha P_j + \gamma O_{i,j} + \alpha^{\times}(P_j \times O_{i,j}) + \delta L_{i,j} + \delta^{\times}(L_{i,j}^{\times}) + \beta_{dist} D_j + \beta_{dist}^{\times}(D^{\times}) + \beta_{control} X_{i,j} + \varepsilon_{i,j} \tag{3.1}$$

[14] As a robustness check we also estimate this relationship using logistic and linear probablility regression models and as expected, the results are not affected by the choice of estimaiton model.

Here, i represents individual women in the household j. $Y_{i,j}$ is our outcome of interest, which takes value 1 for obesity if BMI≥25, and 0 otherwise. The model includes a constant β_0 and a stochastic error term ε. The parameters α, γ, β_{dist}, δ, and $\beta_{control}$ quantify the effects of variables in the vectors P, O, L, D, and X. The vector P contains quartiles of the share of calories consumed from semi- and ultra-processed foods ($P = q_s, q_u$); O contains categorical variables for the occupation of women as a proxy for their physical activity level; L contains variables that represent lifestyle characteristics– livelihood strategy of household and education of women ($L = i_l, i_e$); D contains two variables that measure the distance from the village center to Bangalore city and closest town ($D = d_{Bangalore}, d_{Towns}$); and X contains the control variables presented in Table 3.1.

We also allow for interaction effects between some of these variables. The interaction terms are represented by the superscript "×" to the respective parameters and vectors in equation (3.1). One such interaction is estimated between the share of semi- and ultra-processed calories and the occupation of women, $P \times O = (i_c \times O,\ i_u \times O)$, to test whether the relationship between processed food and obesity is mediated by physical activity level. Increased participation in the off-farm employment sector increases dietary diversity and sedentary activities, leading to greater obesity (Popkin, 2006; Popkin and Gordon-Larsen, 2004; Rahman and Mishra, 2020). Besides, the off-farm working environment might also foster awareness of healthy eating and exercise practices, and educated women living in these off-farm households might value this awareness positively and incorporate them in their day-to-day activities than uneducated women (Cawley, 2015). Such an effect of lifestyle change is estimated by the interaction variable between household livelihood strategies and the education of women – $L^{\times} = (i_l \times i_e)$. The economic growth of urban center increases obesity among people living in the vicinity (Aiyar et al., 2021). The interaction between the two distance variables, $D^{\times} = (d_{Bangalore} \times d_{Towns})$ estimates the effect of proximity to urban cener on obesity. A larger value in this interaction variable indicates that the village is remote to both Bangalore city and small town.

3.5. Results

3.5.1. Main regression analysis

Table 3.2 presents the regression results for the relationship between the consumption of calories from processed foods and obesity. The results show that, compared with quartile 1, the semi-processed food calories at the highest quartiles of consumption (quartile 4) increases the prevalence of obesity among women. Unlike the evidence from developed countries (Asfaw, 2011; Monteiro et al., 2018; Moubarac et al., 2013; Poti et al., 2017) we find that ultra-processed food calories do not matter for obesity. As we proposed in section 2.1, this relationship could be driven by a higher income elasticity of semi-processed food (relative to ultra-processed foods) that leads to greater consumption of semi-processed foods at lower incomes. Or, combined with greater affordability through the PDS and a lower opportunity cost of time of home-cooking (as compared with higher-income groups), semi-processed foods may be the 'processed food of choice' in the diets of lower-income groups. Hence, they constitute a greater share of the household's diet. Excess consumption of semi-processed foods (as seen in Table 3.2) even in the presence of ultra-processed foods may thus create a greater risk for obesity in these peri-urban areas.

Table 3.2: Association of processed food calories with obesity – probit regression estimates

VARIABLES	Obesity
Semi-processed calories (%) (ref. Quartile 1)	
Quartile 2	-0.01 (0.95)
Quartile 3	0.04 (0.75)
Quartile 4	**0.24* (0.08)**
Main occupation (ref. Housewife)	
Office work	-0.21 (0.57)
Labor intensive work	-0.15 (0.61)
Student	0.08 (0.87)
Semi-processed calories (%) X Main occupation (ref. Quartile 1 X Housewife)	
Quartile 2 X Office work	0.25 (0.52)
Quartile 2 X Labor intensive work	0.21 (0.50)
Quartile 2 X Student	-1.02 (0.10)
Quartile 3 X Office work	0.06 (0.87)
Quartile 3 X Labor intensive work	-0.17 (0.59)
Quartile 3 X Student	-0.11 (0.82)
Quartile 4 X Office work	0.30 (0.42)
Quartile 4 X Labor intensive work	**-0.65* (0.06)**
Quartile 4 X Student	**-1.43** (0.02)**
Ultra-processed calories (%) (ref. Quartile 1)	
Quartile 2	0.18 (0.17)
Quartile 3	0.14 (0.29)
Quartile 4	0.09 (0.49)
Ultra-processed calories (%) X Main occupation (ref. Quartile 1 X Housewife)	
Quartile 2 X Office work	0.15 (0.70)
Quartile 2 X Labor intensive work	0.01 (0.98)
Quartile 2 X Student	-0.12 (0.83)
Quartile 3 X Office work	0.25 (0.50)
Quartile 3 X Labor intensive work	0.37 (0.28)
Quartile 3 X Student	0.46 (0.40)
Quartile 4 X Office work	-0.12 (0.76)
Quartile 4 X Labor intensive work	0.06 (0.86)
Quartile 4 X Student	-0.01 (0.99)
Distance to Bangalore (km)	-0.01 (0.63)

Distance to the closest town (km)	0.04 (0.30)
Distance to Bangalore X Distance to the closest town	-0.00 (0.32)
Household livelihood strategy (ref. Pure farm)	
Pure off-farm	**-0.30** (0.02)**
Composite (farm and off-farm)	**-0.35*** (0.01)**
Others	-0.15 (0.57)
Literacy of women (dummy – No education)	-0.21 (0.25)
Household livelihood strategy X Education of women	
Pure off-farm X No education	**0.47** (0.02)**
Composite (farm and off-farm) X No education	0.22 (0.33)
Others X No education	0.18 (0.71)
Controls	
Age (years)	**0.01* (0.08)**
Marital status (ref. Married)	
Unmarried	-0.23 (0.25)
Divorced/widowed	-0.01 (0.94)
Number of children (count)	**0.07*** (0.01)**
Household members (count)	0.03 (0.12)
Caste (ref. General)	
SC & ST	-0.08 (0.41)
OBC	0.21 (0.02)
Assets (count)	**0.12*** (<0.01)**
Grocery purchase from modern food outlets (%)	0.00 (0.44)
Main grocery shopper (ref. Adult female)	
Adult male	-0.13 (0.18)
Anybody in the family	0.06 (0.64)
Toilet (dummy - yes)	0.15 (0.16)
Transect (dummy - South)	**-0.26*** (0.01)**
Constant	**-1.37*** (0.01)**
Mean obesity	0.36
Pseudo R-squared	0.12
LR statistic	**210 (<0.01)**
Observations	1,335

Note: ***p<0.01, **p<0.05, *p<0.1. p-values in parentheses.

To estimate the proposed argument in section 3.2.1, we test the relationship between processed foods and obesity by household asset quartiles. The results are presented in Table 3.3. The household assets can be used to measure the socioeconomic status (SES) of individuals, with higher assets implying higher SES (Gwatkin et al., 2007). SES of individuals has been linked with dietary preferences in LMICs like India with the rich consuming more ultra-processed foods due to greater affordability of the same (Daniel et al., 2011; Green et al., 2016; Satija et al., 2015). In table 3.3, we see that obesity in upper-middle SES households is driven by the consumption of calories from semi-processed foods. But, similar to high-income countries, it is the share of calories from ultra-processed foods that are correlated with obesity among high SES households. Combined with the results from Table 3.2, this indicates that at the early to middle stages of economic development, as represented by households living in our study context of peri-urban areas, semi-processed food consumption may be driving obesity. At higher levels of development, this relationship becomes an outcome of the ultra-processed food consumption as typically seen in high-income countries.

Table 3.3: Association of processed food calories with obesity by income level of the households

VARIABLES		Low	Low-middle	Upper-middle	High
Semi-processed calories (%) (ref. Quartile 1)					
	Quartile 2	0.03 (0.89)	-0.22 (0.28)	-0.18 (0.48)	0.01 (0.98)
	Quartile 3	-0.13 (0.49)	0.01 (0.98)	0.28 (0.27)	-0.32 (0.51)
	Quartile 4	0.02 (0.91)	-0.08 (0.72)	**0.51** (0.04)**	-0.24 (0.61)
Ultra-processed calories (%) (ref. Quartile 1)					
	Quartile 2	0.14 (0.51)	0.10 (0.62)	0.41 (0.13)	0.27 (0.46)
	Quartile 3	0.21 (0.27)	0.24 (0.27)	0.04 (0.88)	**0.67* (0.07)**
	Quartile 4	-0.05 (0.79)	0.10 (0.63)	0.14 (0.63)	-0.10 (0.79)
Constant		0.46 (0.61)	-0.75 (0.52)	-0.43 (0.74)	-0.39 (0.85)
Mean obestity		0.24	0.36	0.42	0.5
Mean assets		4.2	6.0	7.0	8.4
Pseudo R-squared		0.10	0.13	0.16	0.24
LR statistic		**55.80 (<0.01)**	**68.59 (<0.01)**	**67.93 (<0.01)**	**60.62 (<0.01)**
Controls		Yes	Yes	Yes	Yes
Observations		475	378	301	179

Note: ***p<0.01, **p<0.05, *p<0.1. p-values in parentheses.

Controls include main occupation of women, distance to Bangalore city and closest town (and the interaction variable between the two), lifestyle characteristics (livelihood strategies and education), age, marital status, number of children, household size, caste, supermarket food purchases, person purchasing the food, access to toilet, and transect dummy

Another potential explanation for the differences between lower, middle, and higher SES could be access to semi-processed foods. A recent study for Karnataka shows the ration card holders rely more on the energy-dense foods purchased at a subsidized price in PDS and open markets (Cunningham et al., 2021). Table 3.4 shows what happens to obesity in households that hold ration cards when exposed to processed foods. BPL ration cardholders, who are entitled to the largest share of benefits from PDS, are at greater risk of obesity due to excess consumption of calories from semi-processed foods. APL ration cardholders (not poor but feel food insecure in some cases), who are entitled to a small quantity of subsidized staples by PDS, are likely to obese due to consumption of excess calories from ultra-processed foods. Both semi- and ultra-processed foods appear to reduce obesity in non-ration cardholders. The non-ration cardholders who are considered to have higher SES might consume a better quality diet (Cunningham et al., 2021). Thus, counter-intuitively, it would seem that the rationing through PDS, which was established to eradicate hunger in India, now enables people to consume excess energy-dense foods (either through staples such as rice and wheat or through semi-processed foods such as sugar and oil). In these peri-urban food markets, rethinking the current subsidies that enable greater consumption of semi-processed foods may be important. Moving away from semi-processed foods to providing fresh foods could be a solution as experts work on strengthening the PDS to improve urban food security.

Table 3.4: Association of processed food calories with obesity by ration cards

VARIABLES	BPL card	APL card	No ration card
Semi-processed calories (%) (ref. Quartile 1)			
Quartile 2	0.09 (0.42)	0.15 (0.89)	**-1.39*** (<0.01)**
Quartile 3	0.08 (0.51)	-1.11 (0.22)	-0.86 (0.11)
Quartile 4	**0.28** (0.03)**	-0.17 (0.82)	**-1.21** (0.02)**
Ultra-processed calories (%) (ref. Quartile 1)			
Quartile 2	0.17 (0.16)	**1.71** (0.04)**	**-1.26** (0.02)**
Quartile 3	0.19 (0.12)	-1.48 (0.16)	0.17 (0.72)
Quartile 4	0.11 (0.41)	-0.98 (0.30)	-0.28 (0.49)
Constant	-1.06 (0.10)	5.31 (0.22)	0.04 (0.98)
Mean obestity	0.33	0.51	0.37
Mean card holders	0.82	0.06	0.11
Pseudo R-squared	0.11	0.43	0.26
LR statistic	**156.26 (<0.01)**	**50.29 (<0.01)**	**53.21 (<0.01)**
Controls	Yes	Yes	Yes
Observations	1097	83	149

Note: ***p<0.01, **p<0.05, *p<0.1. p-values in parentheses.

Controls include main occupation of women, distance to Bangalore city and closest town (and the interaction variable between the two), lifestyle characteristics (livelihood strategies and education), age, marital status, number of children, household size, caste, asset index, supermarket food purchases, person purchasing the food, access to toilet, and transect dummy

Overconsumption of ultra-processed foods has been identified as a major risk factor for obesity in high-income countries. Similarly, we check if the overconsumption of semi-processed foods in the relationship of dietary adequacy matters to obesity. In Table 3.5, we present the effect of processed foods on obesity in calorie adequate and inadequate households. As expected, we find that excess consumption of semi-processed food calories (quartile 4) is strongly associated with obesity in calorie adequate households. Consumption of calories from processed foods does not affect the likelihood of obesity for those in calorie inadequate households whose calorie consumption is below their RDA. This highlight that there is a threshold in the form of one's baseline ability to meet their RDA for calories, beyond which excess consumption of processed foods is associated with obesity.

Table 3.5: Association of processed food calories with obesity by calorie adequacy of households

VARIABLES		Calorie adequate	Calorie inadequate
Semi-processed calories (%) (ref. Quartile 1)			
	Quartile 2	0.04 (0.79)	-0.20 (0.44)
	Quartile 3	0.09 (0.53)	-0.02 (0.92)
	Quartile 4	**0.39** (0.01)**	-0.16 (0.55)
Ultra-processed calories (%) (ref. Quartile 1)			
	Quartile 2	0.15 (0.35)	0.24 (0.33)
	Quartile 3	0.13 (0.42)	0.16 (0.54)
	Quartile 4	0.18 (0.28)	-0.18 (0.42)
Constant		**-1.39** (0.05)**	-0.94 (0.39)
Mean obestity		0.35	0.36
Mean households		0.29	0.71
Pseudo R-squared		0.13	0.13
LR statistic		**168.12 (<0.01)**	**66.16 (0.03)**
Controls		Yes	Yes
Observations		923	372

Note: ***p<0.01, **p<0.05, *p<0.1. p-values in parentheses.

Controls include main occupation of women, distance to Bangalore city and closest town (and the interaction variable between the two), lifestyle characteristics (livelihood strategies and education), age, marital status, number of children, household size, caste, asset index, supermarket food purchases, person purchasing the food, access to toilet, and transect dummy

A well-known way to alleviate the risks from overconsumption is the role of exercise (Dang et al., 2019; Monda et al., 2008; Popkin, 2009). In our study context, while the direct effect of occupation on obesity is not statistically significant, its interaction with semi-processed food calories shows interesting patterns (Table 3.2). The relationship between excess consumption of semi-processed food calories and obesity is weak for women engaged in labor-intensive work and for students relative to housewives in quartile 1. This indicates that the physical activity of women may moderate the relationship between semi-processed food calories and obesity. That is, for women engaged in labor-intensive work such as farming and/or casual labors and for students, who might do sports and other forms of exercise at their educational institutions, excess consumption of semi-processed food calories appears to be expended by relatively more physical activities.

Diversification of income is also known to influence the diet diversification of households (Rahman and Mishra, 2020). Off-farm employment is associated with a greater sedentary lifestyle, which is correlated with obesity (Popkin, 2009; Popkin and Gordon-Larsen, 2004). In our study context, we find that relative to pure farm households, pure off-farm and composite (farm and off-farm) households are less likely to have obese women (Table 3.2). There can be two possible explanations for this result. First, as discussed by Pingali and Khwaja (2004), increased income through off-farm employment initially can lead to improved diet quality. This may allow households to improve diets without affecting obesity. Second, off-farm employment might also bring some lifestyle changes such as eating more nutritious food and/or more exercise habits that reduce obesity (Cawley, 2015; Popkin, 1999). This can be explained by the estimated interaction effect between livelihood strategies of households and education of women. Uneducated women in pure off-farm households are more likely to be obese than educated women. This indicates that education of women moderates the effect of lifestyle changes that accompany off-farm employment on obesity.

In addition to the factors explained above, some of the individual-level (age and number of children) and household-level (assets and caste) controls are significantly associated with obesity (Table 3.2). That is, older women and women with more number of children are more likely to be obese. The higher economic status of the household increases the incidence of obesity. Women in the OBC caste category are more likely to be obese than the General caste category. Furthermore, women from the Northern research transect are more likely to obese.

3.5.2. Endogeneity between processed foods and obesity

There are few limitations of this study. It is possible that the relationship between processed foods and obesity proposed might not be exogenous due to unobserved heterogeneous factors and potential reverse causality between the two variables. The cross-sectional nature of our data limits our ability to account for such unobserved factors. To account for this potential endogeneity through the instrumental variable (IV) regression method, we need valid instruments. We tried applying the IV method using relevant instruments that we could create from our data set (mean share of expenditure made on processed foods in a village and the percentage of households in a village who eat their meals outside the home) and estimate the causal relationship between processed foods and obesity. However, the tests for the endogeneity of regressors fail to reject the null hypothesis that the variables on the share of calories from semi- and ultra-processed food are exogenous. Thus, we do not consider these estimations as our main results, instead, provide them in Appendix 3.4 for reference. Future research can try to address this limitation by using strong instruments such as the distance to the nearest supermarket and/or by using panel data. Furthermore, since the calories from processed foods in our study are measured at the household level, we can draw no conclusions on the intra-household distribution of processed food calories and its relevance to obesity. However, our results even at the household level show interesting patterns between processed foods and obesity at the early to middle stage of ST, as observed in India. Estimating the effect of individually processed calorie intake on obesity can be one of the recommendations for future research.

3.6. Discussion and conclusion

We analyze the relationship between processed food consumption and obesity in India. Even though there has been a more than 100 percent increase in the prevalence of obesity in India, the literature explaining the same is limited. This paper contributes to the literature discussing obesity in India by providing evidence on how increased processed food consumption due to dietary transition is associated with the increased prevalence of obesity in the Indian peri-urban context. For this, we use primary survey data on food consumption and obesity of women in the rural-urban interface of the mega-city of Bangalore. In the empirical analysis, controlling for possible confounding factors, we model how the share of calories consumed from semi- and ultra-processed foods are associated with the prevalence of obesity among women.

The regression results provide three important insights on the role of processed foods in the rising prevalence of obesity in India. The first, unlike the evidence from developed countries, it is not ultra-processed but semi-processed foods that are significantly associated with increasing obesity in peri-urban India. This relationship between semi-processed food calories and obesity is stronger among lower-income groups (Table 3.3) and among BPL ration card holders that procure subsidized semi-processed foods from PDS (Table 3.4). Since semi-processed foods are widely consumed in everyday diet, an increase in income enables households, especially the ones in the lower-income groups, to consume excess quantities of semi-processed food items. Furthermore, the distribution of semi-processed foods such as sugar and oil through PDS at subsidized prices improves their access and affordability for lower-income groups. Thus, even in the presence of ultra-processed foods, semi-processed foods drive the risks for obesity in the peri-urban areas in India. These results also highlight that diet-related nutrition challenges faced by India are occurring at a much lower level of dietary transition. However, the diet correlates of obesity shift to ultra-processed foods once the households enter into the higher-income group. This might be due to the improved affordability of ultra-processed foods and the higher opportunity costs of cooking food at home for higher-income households (than the lower-income groups).

Second, there is a threshold effect in the relationship between processed food consumption and obesity. For those who consume lower than the RDA, there is no effect of the consumption of semi-processed foods on their obesity. This relationship turns significant only when women meet their RDA for calories (calorie adequate). Thus, RDA for calories creates a threshold after which obesity becomes linked with dietary preferences for processed foods. This result calls into question a monolithic view that all processed foods are bad for health. The existence of the threshold implies that targeting nutrition information on weight management and calorie consumption for women at early stages of economic development may be a key input into preventing the obesity epidemic from reaching lower-income groups. Research on the dietary and economic effects of processed foods on BMI and health also needs to account for this threshold.

Third, the relationship between semi-processed food calories and obesity is mediated by the physical activity level of women. In line with the broader literature (Dang et al., 2019; Monda et al., 2008; Popkin, 2009), our results show that engaging in relatively labor-intensive physical activities reduces obesity among women who consume excess semi-processed food calories. The results also suggest that off-farm employment characteristics of the households might bring lifestyle changes that help to reduce obesity. These effects, further, moderated by the education of women, with low literate women being at a higher risk to be obese.

The findings of our study provide a descriptive exposition on the role of processed foods in the dietary transition and the increasing prevalence of obesity. We propose two policy recommendations based on this research. The first is to improve the awareness, access, and affordability of fresh, unprocessed or minimally processed foods. Even though a few semi-processed foods such as sugar and oil are provided to people at cheap prices through PDS, overconsumption of these foods, in turn, increases obesity. Thus, it is important to encourage people to invest in eating healthy foods and other health-enhancing behaviors by subsidizing healthy food. Our estimates provided in Appendix 3.5 support this suggestion by showing that unprocessed or minimally processed foods reduce the prevalence of obesity. Pre-emptive action through greater awareness may be key to stem the obesity epidemic. Second, since we show that physical activity levels and education moderate the effect of processed foods on obesity. We also hypothesize that the obesity alleviating effects among higher-income groups may come from their ability to engage in health behaviors like exercising. Educating people to engage in healthy lifestyle choices is an important input to reduce obesity in a rapidly evolving peri-urban context. As individuals increase their income levels due to economic growth opportunities, targeting interventions to increase awareness in their diet and lifestyle may be a key input for nutrition policy in LMICs like India.

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Appendix

Appendix 3.1: t-tests for mean differences between women with and without BMI information in the sample.

Variable	t-tests	
	Without BMI	With BMI
Age	39	38
Literacy	1.3	1.3
Marital status	1.5***	1.2
Occupation	1.8***	1.5
Additional occupation	1.9***	1.4
Religion	1	1
Caste	2.1	2.1
Family size	6***	5
Asset_index	5.6**	5.8
Ration card	2	3
Vegetarian family	1.9	1.9
Person buying food	1.9	1.9
% of food purchased from modern food outlets	17.5***	22.2
Livelihood strategy	2.1	2.1
Bathroom	1.6	1.6
Toilet	0.8	0.8
Distance to Bangalore	26.9**	25.4
Distance to nearest towns	11.3	11.6
Transect	1.5	2.4

Note: *** significant at P-value<0.01, ** significant at p-value<0.05

Appendix 3.2: t-test for women with and without missing covariates

	t-tests	
Variable	BMI for missing covariate	BMI for non-missing covariate
Marital status	22.1	22.4
Occupation	22.7	23.4
Additional occupation	23.7	23.4
Caste	25	23.4
Ration card	22.6	23.4
Bathroom	23.3	23.4
Toilet	24.1	23.4
Vegetarian family	25.5	23.4
Person buying food	24.8	23.4
% of food purchased from modern food outlets	24.5	23.4

Note: *** significant at P-value<0.01, ** significant at p-value<0.05

Appendix 3.3: Summary of food items classified under 3 food groups of NOVA classification system

Unprocessed or minimally processed food	*Semi-processed food*	*Ultra-processed food*
• **Cereals:** Rice; Wheat; Bajra; Ragi; Jowar; Small millets; Maize; Barley • **Vegetables:** Potato; Onion; Radish; Carrot; Turnip; Beetroot; Sweet potato; Arum; Pumpkin; Gourd; Bitter gourd; Cucumber; Parwal; Ridge gourd; Snake gourd; green papaya; Cauliflower; Cabbage; Brinjal; Lady's finger; Spinach; Salad; French beans; Tomato; Chillies; Capsicum; Green plantain; Green jackfruit • **Fruits:** Lemon; Banana; Kiwi; Jackfruit; Watermelon; Pineapple; Coconut; Guava; Water chestnut; Orange; Papaya; Mango; Melon; Pears; Berries; Lichi; Apple; Grapes; Pomogranet; Chiku • **Dry fruits and nuts:** Groundnut; Dates; Cashewnut; Walnut; Raisin; Almond • **Animal products:** Eggs; Mutton; Pork; Chicken; Fish; Beef; Milk liquid; Milk condensed/powder; Curd • **Spices:** Honey; Garlic; Ginger; Tamarind; Curry leaves; Oilseeds; Turmeric; Black pepper; Curry leaves; Dry chilies • **Drinks:** Homemade fruit juice; Tea; Coffee	• Refined wheat flour • Ghee • Butter • Sugar • Jaggery • Salt • Mustard oil; Groundnut oil; Edible oil • Chira/Awlaki • Puri/Kadle puri • Suji • Sewai/vermicelli	• Bread • Ice cream • Candy • Margarine • Lemonade • Purchased juice • Cola Mazaa • Biscuits • Cake/Pastry • Purchased sweets • Salted refreshments • Sauce • Jam, Jelly • Maggi noodles • Paratha (packaged) • Roti (Packaged) • Pizza • Burger • Chicken nugget • Wraps • Rolls • French fries • Frozen food • Pickles

Appendix 3.4: IV-probit regression for the effect of processed food calories on obesity

The main challenge in IV regression is finding valid instruments that meet two criteria. First, the instrument should be highly correlated with the variables on the share of semi- and ultra-processed foods. Second, the instruments should not be correlated with any of the unobserved factors affecting obesity in women. Thus, the instruments chosen should be directly related to processed foods but not directly related to obesity. We identified—the mean share of expenditure made on processed foods in a village and the percentage of households in a village who eat their meals outside home—as two instruments to apply IV-probit regression. We argue that households tend to eat more processed foods if they live in a community where other households also eat more processed foods through their social contacts. Thus, households in a village with an average high share of expenditure on processed food might tend to consume more processed foods due to the influence of their neighbors. Furthermore, meals eaten outside the home are often processed and convenient to eat. Thus, households in a village with a greater share of eating out practice might also tend to eat meals outside the home. Using these two instruments we apply IV-probit regression to estimate the effect of shares of calories from semi- and ultra-processed foods on obesity. The results (presented below) show that the shares of calories from semi- and ultra-processed foods do not significantly affect obesity. However, the tests for the endogeneity of regressors fail to reject the null hypothesis that the variables on the share of calories from semi- and ultra-processed food are exogenous. For robustness check, we ran the estimations using a two-stage linear regression model with BMI of women as an outcome variable. The results and tests of endogeneity (not present here) remain the same. Since there is no endogeneity; a standard probit model is suitable in this situation. Thus, we consider the probit regression estimations as our main results.

VARIABLES		Obesity
Semi-processed calories (%)		-0.16 (0.77)
Ultra-processed calories (%)		0.29 (0.76)
Main occupation (ref. Housewife)		
	Office work	0.12 (0.66)
	Labor intensive work	0.07 (0.92)
	Student	0.08 (0.96)
Age (years)		0.02 (0.61)
Marital status (ref. Married)		
	Unmarried	-0.22 (0.46)
	Divorced/widowed	-0.21 (0.75)
Number of children (count)		0.06 (0.49)
Household members (count)		0.03 (0.35)
Caste (ref. General)		
	SC & ST	-0.49 (0.73)
	OBC	0.36 (0.43)

Assets (count)	0.22 (0.49)
Household livelihood strategy (ref. Pure farm)	
Pure off-farm	-0.23 (0.51)
Composite (farm and off-farm)	-0.42 (0.24)
Other income sources	0.66 (0.81)
Education of women (dummy - No)	-0.39 (0.46)
Household livelihood strategy X Education of women	
Pure off-farm X No education	0.65 (0.31)
Composite (farm and off-farm) X No education	0.05 (0.94)
Others X No education	-0.64 (0.82)
Main grocery shopper (ref. Adult female)	
Adult male	-0.15 (0.49)
Anybody in the family	-0.05 (0.91)
Toilet (dummy - yes)	0.18 (0.49)
Distance to Bangalore (km)	-0.01 (0.68)
Distance to the closest town (km)	0.02 (0.78)
Distance to Bangalore X Distance to the closest town	-0.00 (0.95)
Transect (dummy - South)	-0.22 (0.25)
Constant	-0.51 (0.86)
Mean obesity	0.36
Test of endogeneity of share of semi- and ultra-processed calories: H_0: Regressors are exogenous	
Wald chi-square test of exogeneity	0.23 (0.89)
Observations	1,335

Note: ***p<0.01, **p<0.05, *p<0.1. p-values in parentheses.

Appendix 3.5: Association of unprocessed food calories with obesity

VARIABLES		Obesity
Unprocessed calories (%) (ref. Quartile 1)		
	Quartile 2	-0.16 (0.21)
	Quartile 3	-0.08 (0.54)
	Quartile 4	**-0.27** (0.04)**
Constant		**-1.04* (0.06)**
Obesity (%)		0.36
Pseudo R-squared		0.11
LR statistic		**204.53 (<0.01)**
Controls		Yes
Observations		1,335

Note: ***p<0.01, **p<0.05, *p<0.1. p-values in parentheses.

Controls include main occupation of women, distance to Bangalore city and closest town (and the interaction variable between the two), lifestyle characteristics (livelihood strategies and education), age, marital status, number of children, household size, caste, asset index, supermarket food purchases, person purchasing the food, access to toilet, and transect dummy

4. You eat what you work – livelihood strategies and nutrition in the rural-urban interface

Anjali Purushotham, Linda Steinhübel

Under review in *World Development*

Abstract:

To understand how rural transformation affects smallholder welfare, it is important to understand the links between household livelihood strategies and nutrition. As cities all over the world grow, an increasing number of smallholders find themselves in the interface between rural and urban areas where they are confronted with trade-offs in decision making regarding production (agricultural operations vs. off-farm employment) and consumption (own produced vs. purchased food from different markets). In such contexts, we are particularly interested in the full composite effect of different employment choices on household nutrition—an aspect often neglected in the literature. To do so, we propose a conceptual framework that considers agricultural production for own consumption, income-generating agricultural operations and off-farm employment, and the role of market access in explaining household nutrition. Then, we use primary socio-economic survey data from the rural-urban interface of Bangalore, a megacity in southern India, to test the interactions displayed in the conceptual framework. We apply a multivariate regression for household-level nutrient adequacy ratios (HNARs) of three macronutrients (calories, protein, and fat) and three micronutrients (vitamin A, iron, and zinc). Our results show that the mix of different agricultural operations and off-farm employment are important to explain households' nutritional status. Furthermore, our results imply that the relationship between income generated through agriculture and off-farm employment and nutrition is non-linear, with a threshold, beyond which further increase in income associated with overnutrition. Also, we find that undernutrition is most prevalent in socio-economically disadvantaged households.

Keywords: livelihood strategies, nutrition transition, nutrient adequacy ratio, multivariate regression, rural-urban interface.

4.1. Introduction

Rural livelihoods are changing in many low- and middle-income countries (LMICs) around the world. Urbanization, improved infrastructure, and access to new technologies are just some of the factors changing the way smallholder households earn a living and shape their lives (Schneider and Woodcock, 2008; Vandercasteelen et al., 2018). Literature shows that once provided with better market access, smallholder households are likely to diversify their livelihood strategies and that there are trade-offs in household decision-making regarding the allocation of labor into the farm and/or off-farm sectors (Diao et al., 2019; Steinhübel and Cramon-Taubadel, 2020). This can mean a shift from labor-intensive subsistence agriculture to commercialized agricultural operations (Damania et al., 2017; Pingali, 2007a; Vandercasteelen et al., 2018) and/or an increased share of household labor allocated into off-farm employment (Deichmann et al., 2009; Fafchamps and Shilpi, 2003; Haggblade et al., 2010).

Of developmental relevance is the question of how these changes in employment affect the living standards and food security of smallholder households. Several studies have analyzed the effects of commercialized agriculture and off-farm employment on household income and living standards, generally finding a positive association (Haggblade et al., 2010; Imai et al., 2015; Ogutu and Qaim, 2019; Pfeiffer et al., 2009). The patterns often become complex when it comes to their effect on household food security and nutrition.

The existing literature on the link between smallholder employment and food security can generally be divided into two strands. The first addresses the role of agricultural operations on household food security. The second strand is concerned with the effects of off-farm employment.

Regarding agricultural operations, some studies emphasize increased on-farm production diversity as a means to increase dietary diversity (Ecker, 2018; Jones et al., 2014). However, this link mainly applies to subsistence farmers and becomes weaker when households shift to commercialized agricultural operations (Muthini et al., 2020; Pingali and Sunder, 2017; Sibhatu et al., 2015; Sibhatu and Qaim, 2018). In many cases, households' market participation reduces the role of on-farm production diversity in increasing their dietary diversity (Pingali and Sunder, 2017; Sibhatu et al., 2015). While some studies show that agricultural commercialization improves household nutrition (Cazzuffi et al., 2020; Ntakyo and van den Berg, 2019), the recent evidence suggests a weaker relationship between the two (Carletto et al., 2017; Radchenko and Corral, 2018).

As for the effect of off-farm employment, it increases households' expenditure on diversified diet and leads to improved nutrition security (Babatunde and Qaim, 2010; D'Souza et al., 2020; Owusu et al., 2011; Rahman and Mishra, 2019). However, the forces of urbanization, globalization, access to modern food outlets, and lifestyle change increase the intake of sugar, salt, oil, snacks, and sweetened beverages (Cockx et al., 2018; Pingali, 2007b; Pingali and Khwaja, 2004; Popkin, 1999). Furthermore, participation in off-farm activities increases the opportunity cost of cooking food at home and the consumption of convenience foods away from home (Kennedy and Reardon, 1994; Regmi and Dyck, 2001). The resulting increase in the intake of energy-dense food items together with changes in work effort due to the shift in occupation patterns has lead to multiple forms of malnutrition in many LMICs (Meenakshi, 2016; Popkin et al., 2020).[15] Thus, it is important to understand how different employment choices of households and the resulting income generation are linked to their nutrition from the perspective of malnutrition.

We argue that solely focusing on either the effects of agricultural operations or the effects of off-farm employment is not sufficient to understand the full effect of households' employment choices on their nutritional status. Particularly when households engage in several livelihood strategies at the same time, the net effect of interacting changes in production, income, and consumption decisions can be highly complex. Thus, different employment choices and their combinations, depending on the access to labor, agricultural, and food markets, affect household nutrition in different ways. We visualize this literature gap in Fig. 4.1. Based on recent findings in the literature (Diao et al., 2019; Steinhübel and Cramon-Taubadel, 2020), we argue that most smallholder households will fall in one of the four white boxes (Fig. 4.1) when aligning them according to their (i) agricultural operations and (ii) off-farm employment decisions. This means that households' livelihood depends on a composite of agricultural operations and off-farm employment. However, for studies in the first strand of literature discussed before, boxes (a) and (b) are normally the points of departure. Authors are interested in what happens when farmers move from the box (a) to box (b) not paying much attention to off-farm employment. Studies in the second strand of literature rather place their households in boxes (d) and (e) in Fig. 4.1 analyzing implications of off-farm employment and lifestyle changes on nutrition disregarding remaining agricultural operations of the household.

[15] Until recently malutrition was synonymous with undernutrition/hunger. However, two other forms – overnutrition and micronutrient deficiency – have been included ((Development Initiatives, 2017)). In many cases multiple burdens of manutrition co-exists at individual-, household-, community-, and country-level and they are termed as double burden of malnutrition (co-existence of under- and overnutrition) and triple burden of malnutrition (co-existence of undernutrition, overnutrition, and micronutrient deficiency).

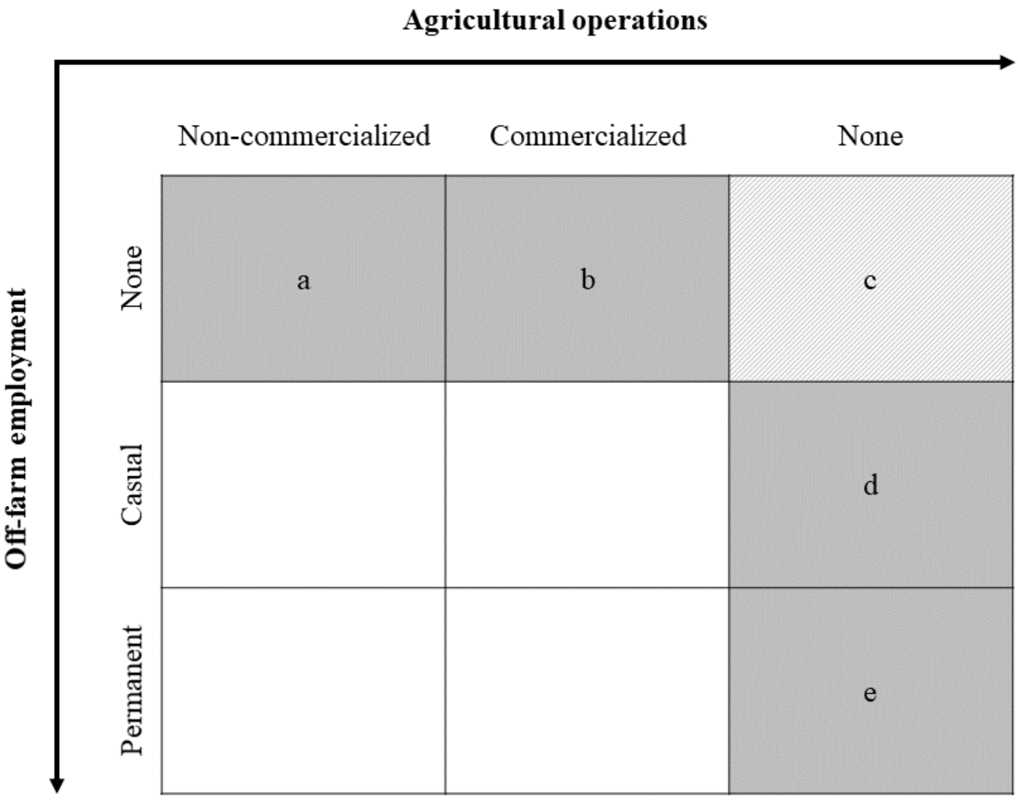


Figure 4.1. Dimensions of household employment choices – agricultural operations vs. off-farm employment

Note: For consistency, we chose the categories in the two dimensions based on the indicators used later in the empirical analysis. Other specifications are possible as well (e.g. skilled vs. unskilled off-farm employment). Households in box (c) are a special case neither employed in the farm nor the off-farm sector.

Thus, we aim to contribute to the literature by explicitly investigating the effect of interactions between smallholders' agricultural operations and off-farm employment choices on their nutritional status. To this end, we propose a framework that considers the full composite of household employment choices—farm and off-farm—and their joint effects on nutrition. We pay special attention to possible effects of access to both, (i) agricultural and labor markets (production and income side) and (ii) food markets (consumption side). We then use primary socio-economic survey data from 941 households in the rural-urban interface of the mega-city of Bangalore in southern India to empirically investigate the pathways illustrated in the conceptual framework. Bangalore region shows exactly the development characteristic representative of many parts of India and other LMICs: a relative decline of the importance of income from the agricultural sector (Chand et al., 2017; Chand et al., 2015; Pingali, 2007a) and a growing casual labor and off-farm sector (Chandrashekar and Mehrotra, 2016; Jatav and Sen, 2013). These transitions in economic activities are driven by the large urban center as well as the growth of small towns and peri-urban areas (Chatterjee et al., 2015;

Himanshu et al., 2011; Li and Rama, 2015; Pingali et al., 2019). This makes the rural-urban interface of Bangalore particularly useful for our analysis of the interactions among household employment choices and their effect on nutrition. By using HNARs for three macronutrients (calories, protein, and fat) and three micronutrients (vitamin A, iron, and zinc), we can investigate the households' nutrient consumption level in a nuanced way.

A multivariate regression framework is the center of our statistical analysis with the HNARs as dependent variables. We group households based on their occupational choices regarding agricultural operations and off-farm employment. Agricultural operations include non-commercialized agriculture, commercialized agriculture, and no agriculture; whereas, off-farm employment is divided into permanent, casual, or no employment in the off-farm sector of at least one adult household member (>16 years of age). Allowing for interaction between these two employments dimensions, we obtain a detailed insight into the association of employment choices within a household and its (average) nutrient consumption. Furthermore, we include the distance to Bangalore and the closest small town in our analysis as proxies for market access.

Our results show that the composite effect of agricultural operations and off-farm employment is important in explaining household nutrition. Of particular importance is the combination of commercialized agricultural operations and permanent off-farm employment. Households with such a mix of employment choices display an excess consumption of nutrients. We see a further increase in such excess consumption among households with the aforementioned combination of employment choices that are located closer to the town. This suggests that an increase in income due to households' participation in more than one employment and proximity to urban markets increase the burden of overnutrition. Furthermore, the results indicate that undernutrition is still prevalent among the socio-economically disadvantaged households in this setting of the rural-urban interface.

The remainder of the paper is structured as follows. We set up a conceptual framework to illustrate possible pathways between livelihood strategies and nutrition in section 4.2. In section 4.3, we describe our study area, data set, variable definitions, and statistical analysis employed. In section 4.4, we descriptively elaborate on our sample characteristics and discuss the results. In the final section (section 4.5), we summarize our findings and derive policy implications.

4.2. Conceptual Framework

Several studies show that many smallholder farm households in LMICs rely on some form of off-farm income to supplement their livelihood (Chandrashekar and Mehrotra, 2016; Steinhübel and Cramon-Taubadel, 2020). Thus, the livelihood of these smallholder households should be understood as a composite of different employment choices (commercialized and non-commercialized agricultural operations, any kind of off-farm employment). The share of the respective employment dimension in households' livelihood portfolio will be significantly influenced by their access to agricultural input and output markets as well as to access to labor markets (Fafchamps and Shilpi, 2003; Vandercasteelen et al., 2018). Similarly, the diet consumed by households will be affected by their access to food markets (Pingali, 2007b; Reardon et al., 2003). This means households' location has a significant influence on production, income, and household diets, as well as pathways connecting them.

A recent framework presented by Muthini et al. (2020) investigates the interdependencies between market access, farm production diversity, and nutrition. We add to this concept by adding the element of off-farm employment and by differentiating between the market access regarding production and consumption decisions. We indicate this by the two gray boxes in Fig.4.2 and disregard for the moment that anything but market access influences households' employment or diet choices. Hence, a households' employment choices, i.e. the share of labor attributed to agricultural operations (non-commercialized or commercialized) and off-farm employment are influenced by its access to agricultural (input and output) and labor markets (upper gray box). Transportation costs generally decrease for households located closer to any type of market. Thus, Vandercasteelen et al. (2018) and Damania et al. (2017), argue that with proximity to agricultural markets net input prices decrease and net output prices increase, leading to a higher rate of commercialized agriculture closer to markets and cities. On the other hand, Deichmann et al. (2009) and Fafchamps and Shilpi (2003) show that once access to (urban) off-farm markets increases, smallholder households are likely to take up this opportunity and remove some labor force from their agricultural operations. Thus, households often face trade-offs when assigning labor into agricultural operations and/or off-farm employment resulting in potentially complex patterns of employment choices in peri-urban areas (Steinhübel and Cramon-Taubadel, 2020). Therefore, we visualize households' employment choices as a continuum between agricultural operations and off-farm employment in Fig. 4.2 assuming that most smallholder households are located somewhere between the two extremes.

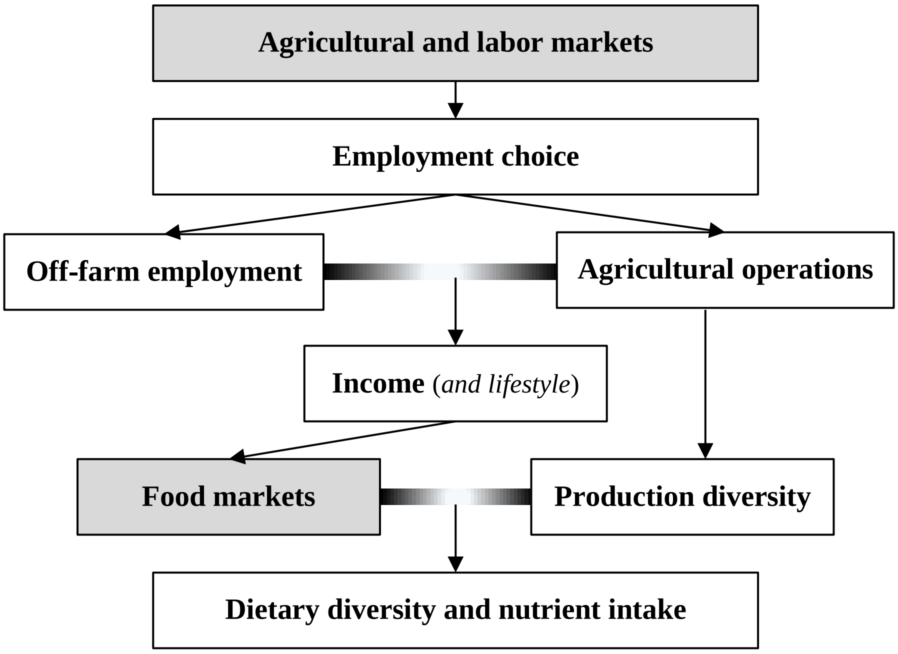


Figure 4.2. Household employment choice, nutrition, and access to markets

Employment choices are linked to household nutrition mainly through two pathways. The first is the subsistence pathway, where the households consume the food crops produced on their farm. The second pathway is income, where households use income generated through agricultural commercialization and off-farm employment to purchase food items from the market. The respective share of either type of economic activity—on-farm production and income generation—will determine how much of households' diet relies on food markets. This is where the access to food markets (second gray box)—which does not have to coincide with access to agricultural and labor markets—comes into play. Note that income-generating employment choices are likely connected to lifestyle changes (e.g. health awareness or opportunity costs of cooking) as well. Thus, next to pure access to food markets, the income pathway to nutrition also relies on the choice made in the market (i.e. which food items are purchased). Households' dietary patterns and nutrient consumption are, therefore, determined by the (subsistence) production diversity as well as the assortment of food markets and outlets available to a household.

4.3. Materials and methods

4.3.1. Study area and survey design

With a population of 9.6 million (Directorate of Census Operations Karnataka, 2011), Bangalore is the fifth most urban agglomeration in India and the city is expanding continuously. Bangalore and several satellite towns, located within a 40-kilometer distance, provide many opportunities for employment in the formal and/or informal off-farm sector. Several highways connecting the urban centers lead to a rise in urbanization patterns in the entire region (Directorate of Census Operations Karnataka, 2011). Nevertheless, agriculture still prevails as a major livelihood strategy for people living in the peripheries and small towns around Bangalore (Directorate of Census Operations Karnataka, 2011). Improved infrastructure and expanding agricultural markets help farmers to intensify their production systems (cultivating crops and rearing dairy cows) beyond just subsistence. Several domestic supermarkets in Bangalore have established collection centers in nearby villages and small towns to procure fresh food products and make them available to urban and peri-urban consumers (Vishnu and Kumar, 2019). Also, such marketing arrangements provide a higher price to the farmers than the price received at the traditional markets and, thus, serve as an incentive for farmers to produce crops for sale.

While undernutrition persists, overweight/obesity and anemia (which is a result of micronutrient deficiency) are rising health concerns in both the Bangalore urban and rural districts (NFHS - 4, 2015-16). This indicates that diet-related health problems in Bangalore are shifting from the burden of undernutrition to overnutrition. One of the mainly attributed factors for this is the transition in the type of diet consumed by the people. Pingali and Khwaja (2004) conceptualize two stages of diet transition associated with economic growth in India. The first stage is characterized by the income-induced shift from the consumption of a few traditional staples (such as rice and wheat) to a diversified diet, leading to improved diet quality. In the second stage, the influence of urbanization and globalization results in excess consumption of sugar, salt, sodium, saturated fat, etc., which is associated with the incidence of overnutrition. Pingali and Khwaja (2004) also highlight that urbanization can have a significant effect on the speed of the shift from the first to the second stage of dietary transition due to the improved access and affordability (rising income levels) of diverse diets. In the Bangalore area, this can be observed in a variety of food outlets, ranging from mom & pop stores to hypermarkets to fast food centers. A recent study by Mittal and Vollmer (2020) shows the double burden of malnutrition crisis in the rural-urban interface of Bangalore.

In this setting, a socio-economic survey of 1275 households provides the basis for our empirical analysis. Our study area comprises two research transects that cut through the rural-urban interface of Bangalore city, as shown in Fig. 4.3. The first transect extends towards the northern part of Bangalore and the second transect extends towards the southwest part of Bangalore.

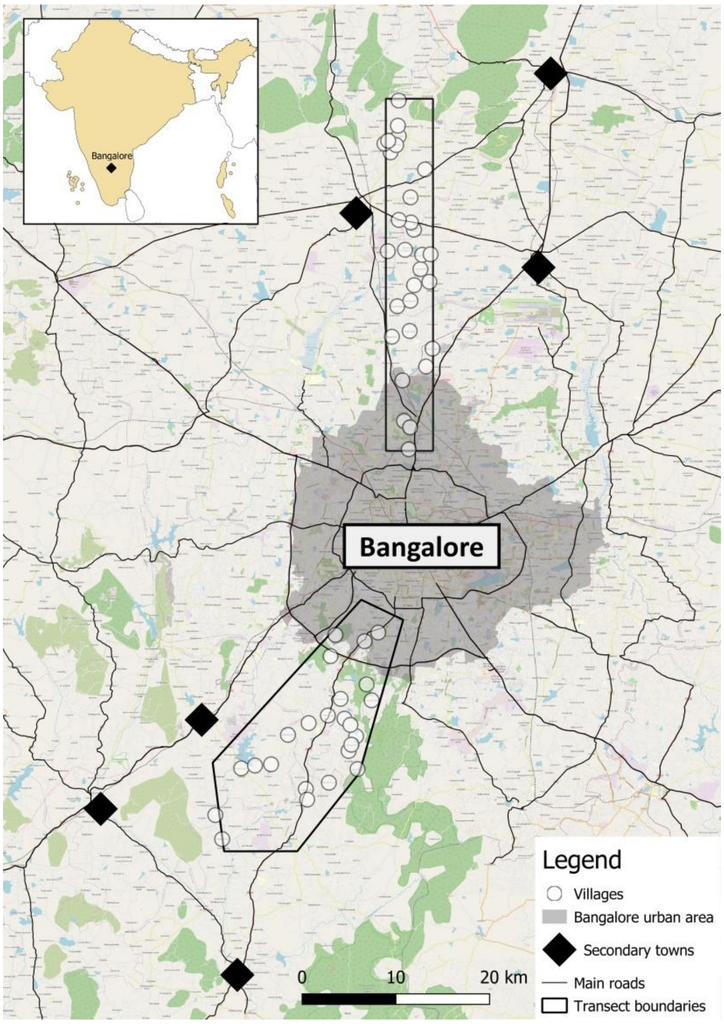


Figure 4.3. Study area, research transects, and sample villages

By applying a two-stage stratified random sampling technique, we ensured that the selected households provide a good representation of urbanization patterns in the area. In the first stage, all villages in each transect were divided into three strata (urban, peri-urban, and rural) using the "Survey Stratification Index (SSI)" constructed by Hoffmann et al. (2017). Then, 10 villages were randomly selected from each stratum, yielding 61 villages in total. In the second stage, the households were randomly selected in each sample village again proportional to their size using a village household list maintained by the publicly run village kinder gardens. All sampled households were interviewed between December 2016 and May 2017 using a comprehensive questionnaire covering socio-demographic, economic, and agricultural information. The respective caregiver of the family was also interviewed to collect the information on food consumption data for the past 14-days of the interview.

Though the survey comprises 1275 households, we were not able to interview caregivers of 152 households. Thus, data on livelihood strategies and food consumption is only available for 1123 households. Furthermore, we did not consider households from eight villages in which none of the sample households reported agricultural production. Agriculture is no longer possible in these villages, which have been integrated into Bangalore as urban wards. Hence, we consider 1004 households from

53 villages in which circumstances allow a choice between agricultural operations and off-farm employment.[16] After dropping the observable outliers of nutrition variables and missing observations of covariates, our empirical analysis is based on a sub-sample of 941 households.

4.3.2. Measurement of nutrition

Household food security is a multidimensional concept and is determined by several factors such as availability, access, and utilization of adequate and appropriate food (Barrett, 2010). As a consequence, measurement is not straightforward and several indicators have been developed. The nutrient adequacy ratio (NAR) and the mean adequacy ratio (MAR) are commonly employed to evaluate nutrient adequacy of diet consumed (Arimond et al., 2010) and validate simple measures of nutrition such as dietary diversity (Steyn et al., 2006; Torheim et al., 2003). However, since NAR and MAR require individual-level dietary recall (commonly 24-hour), data collection is costlier and more time-consuming than the collection of household-level food consumption data for a specific recall period. The adult male equivalent (AME) method is commonly used in the literature to work with household-level data (Babatunde and Qaim, 2010; Ntakyo and van den Berg, 2019). However, recent studies show that it is only a rough proxy of the individual nutrient intake (Coates et al., 2017; Sununtnasuk and Fiedler, 2017; Weisell and Dop, 2012). Connecting both approaches, Schneider and Masters (2019) extend the concept of individual-level NAR and MAR and introduce Household-level NAR and Household MAR to advance the nutrition-related analysis potential using household-level food consumption data.

Since we expect to observe different dimensions of malnutrition in our dataset, MARs are not useful in our case because they are not informative about the under/overconsumption of an individual nutrient. When households experience dietary transition, they tend to consume excess quantities of macronutrients such as calories and fat, and lower amounts of important micronutrients (Pingali, 2007b; Popkin, 1999). Even if they consume recommended quantities of calories there might be too few proteins and important micronutrients consumed (Caulfield et al., 2006). Therefore, we consider HNARs of individual nutrients as dependent variables in our analysis. HNARs are calculated using the 14-day recall household-level food consumption data from our sample. HNARs are calculated for three macronutrients (calories (c), protein (p), and fat (f)) and three micronutrients (vitamin A (v), iron (i), and zinc (z)). We followed the standard approach used in the construction of individual-level NAR to calculate subsequent HNAR measures (INDEX Project, 2018). To calculate the HNAR of nutrient k for household j, we divided the total amount of consumed nutrient k by its recommended dietary allowance (RDA).

[16] We also performed the analysis (section 4.3.5) with the full data set as a robustness check. If at all, the effects presented in section 4.2 turn out stronger. The results are available on request.

$$HNAR_{k,j} = \frac{\text{Amount of nutrient } k \textit{ consumed} \text{ by household } j}{\text{Recommended dietary allowance for nutrient } k \text{ for household } j} = \frac{q_{k,j}}{RDA_{k,j}}$$

where $k = (c, p, f, v, i, z)$.

The quantities $q_{k,j}$ are calculated based on reported quantities of food items consumed for a 14-day recall period in the survey. Nutrient conversion factors for India, summarized in the Indian Food Composition Tables (IFCT) (Longvah et al., 2017), are used to convert the quantities of raw food items into their consumption values for each nutrient k in household j, i.e. $q_{k,j}$. The RDA is commonly given for each individual and it differs by their age, gender, and physical activity level. The RDA for household j is estimated by using demographic information (age and gender) of each household member older than six months to define how much of each nutrient k every household member should ideally consume. We did not have a detailed account of the type of physical activities conducted by each member of our sample households and therefore we considered a moderate level of work for all adult household members.[17] The standardized dietary guidelines recommended by the Indian Council of Medical Research (ICMR) are used to calculate the RDAs for each household member. Then summing up individual RDAs of all household members provided us with an RDA estimate for the household, i.e. $RDA_{k,j}$.

Table 4.1 presents the mean and median values for the HNARs of all six nutrients (distributions are all somewhat skewed with flatter tails to the right). It shows that households on average exceed the consumption of recommended quantities for all these nutrients except vitamin A. Fat scores by far the highest mean and median values; on average households consume 1.6 times more fat than recommended. The average consumption of calories, protein, iron, and zinc come closer to the recommended quantities with the average household (median) overconsuming these nutrients by between 1 and 33 percent. Average vitamin A consumption falls under recommended levels; the average household in our sample only consumes around 60 percent of recommended quantities of vitamin A. These summary statistics and the differences in HNARs highlight the importance of analyzing nutrients separately. Also, observing HNARs much larger (e.g. fats) and smaller (e.g. Vitamin A) than 1 implies that multiple dimensions of malnutrition might pose issues in our study area. Therefore, HNARs of macro- and micronutrients seem to be a suitable proxy to analyze dynamics around nutrition in the rural-urban interface of Bangalore.

[17] Physical activity factor is considered in the RDA of only male and female individuals of 18 years and above, therefore we consider the physical activity factor only for these household members.

Table 4.1. Summary statistics of HNARs of sample households

HNAR for	Obs.	Mean	St. Dev.	Median
Calories	941	1.396	0.565	1.275
Protein	941	1.432	0.613	1.329
Fat	941	2.628	1.431	2.278
Vitamin A	941	0.717	0.431	0.615
Iron	941	1.108	0.535	1.013
Zinc	941	1.373	0.593	1.276

4.3.3. Measurement of livelihood diversification and market access

Following our conceptual framework in section 4.2, the employment choices of the households should play an important role in determining what they eat and, thus, their nutritional consumption. Common classifications in previous studies on employment choices are, for example, formal vs. informal, casual vs. full-time off-farm employment (D'Souza et al., 2020), or commercialized vs. non-commercialized agriculture (Cazzuffi et al., 2020; Sibhatu et al., 2015). Accordingly, we classify our sample households depending on the primary occupation of all household members older than 16 into different categories of agricultural operations and off-farm employment. Agricultural operations relevant in our study area are non-commercialized agriculture, commercialized agriculture (defined as at least one crop sold in 2016), and no agricultural operations at all. These categories are hereafter referred to as non-commercialized, commercialized, and no agriculture households, respectively. Note that these categories are exclusively built on crop management systems. Especially dairy production is common in our study area, with about 54 percent of our households owning dairy cows (Appendix 4.1). We consider this aspect with a separate dummy variable in the subsequent analysis. No agriculture households account for about 40 percent of the sample; whereas another 40 percent of households pursue commercialized and the rest non-commercialized agricultural production (Table 4.2). Off-farm employment is classified into three categories – permanent, casual, and no off-farm employment. In almost two-thirds (62 percent) of all households in our sample, at least one household member works in permanent off-farm employment. Around 30 percent of households do not have any member working in the off-farm employment, i.e. these are pure agricultural households (Table 4.2). About 7 percent of households receive income from casual off-farm employment.

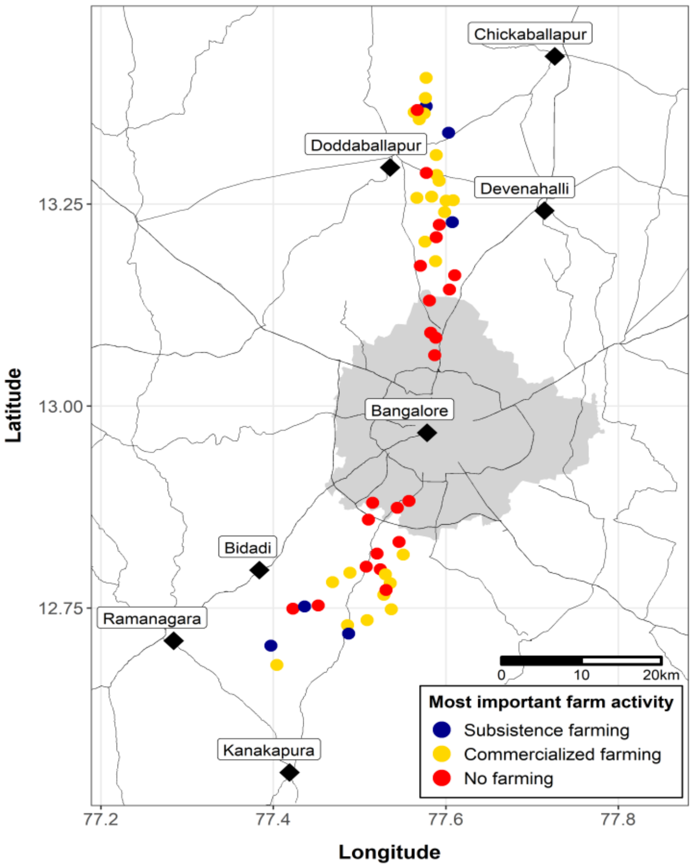
Table 4.2. Cross-table

	Agricultural operations			
	Non-commercialized	Commercialized	No agriculture	TOTAL
Off-farm employment				
No off-farm	98	146	50	294
Permanent	96	199	288	583
Casual	4	26	34	64
TOTAL	198	371	372	941

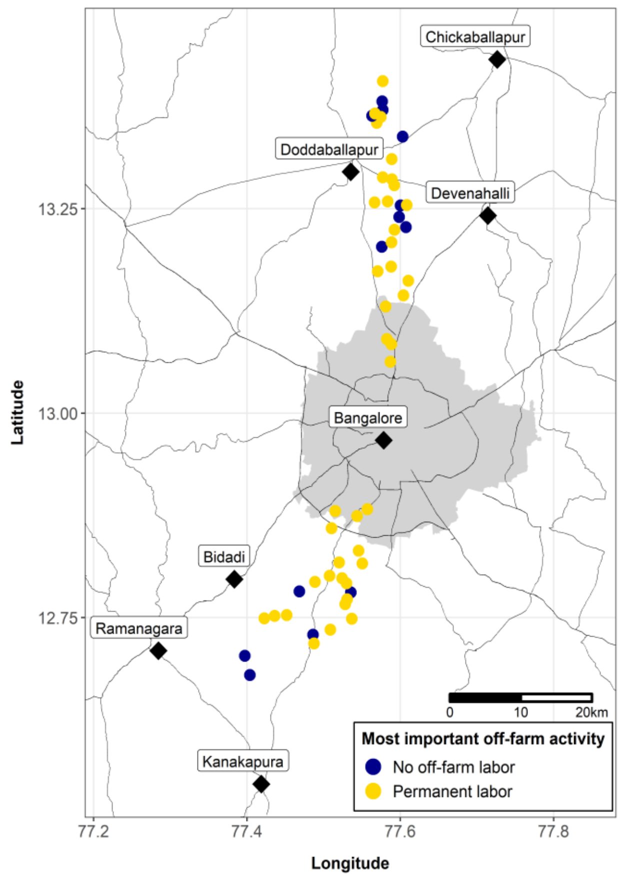
Table 4.2 also presents a cross-tabulation of agricultural operations and off-farm employment. It shows that households with permanent off-farm employment with no agricultural operations are most common (288 households) followed by composite households with permanent off-farm employment and commercialized agriculture (199 households), and commercialized agricultural households with no off-farm employment (146 households). Exclusive non-commercialized agriculture and non-commercialized agriculture combined with permanent off-farm employment each score about 100 households. This implies that we observe a diverse set of different employment choices by households in the rural-urban interface of Bangalore.

Furthermore, when mapping the most common agricultural operations and off-farm employment by village (Fig. 4.4 (a) and (b)), we can see spatial clusters in both employment choices. Permanent off-farm employment appears to be more frequent closer to Bangalore city in both transects (Fig. 4.4 (b)) and agricultural operations seem to be less attractive close to the city. Commercialized agricultural operations are the most common in villages in the center and outer areas of both transect (Fig. 4.4 (a)). Non-commercialized agriculture is only dominant in some villages in the outmost areas of the transects. This observation hints at a spatial gradient radiating from the urban center of Bangalore. This observation coincides with the conceptual framework in section 4.2 (first gray box in Fig. 4.2), where we argue that the gradient/trade-off between on-farm production and income generation depends on access to off-farm labor markets (e.g. permanent off-farm employment) or agricultural markets (e.g. commercialized agriculture).

Considering that access to food markets might affect nutrient consumption (second gray box in Fig. 4.2), we include the distance to Bangalore and distance to the closest town (including Bangalore) as variables measuring market access in our regression analysis.



(a)



(b)

Figure 4.4. (a) Most important agricultural operations in the village; (b) Most important off-farm employment in the village

4.3.4. Control variables

Besides the variables on employment choices and market access, we include household socio-economic characteristics as control variables (Appendix 4.1). This includes the number of household members, the caste of the household, age, gender, literacy of the household head, and the number of durable assets owned by the household. Furthermore, we include variables directly related to food consumption such as the type of ration card owned by the household, the household member typically purchasing food items, and whether the household follows a vegetarian diet. The public distribution system (PDS) established in 1945 has a long tradition in India and aims at achieving food security by providing subsidized access to basic food items (e.g. rice, wheat, sugar, and oil) distributed in government-run shops. By now almost every household has one of two types of ration cards, namely either an above poverty line (APL) or below poverty line (BPL) (NITI Aayog, 2016). In our sample, BPL is the most common (85.3 percent) and only 9.5 percent of the sampled households do not have any ration card. The person buying groceries in the market might also affect household nutritional consumption; a female household member might prioritize the nutritional relevance of food items over its price and convenience more than a male household member (Turrell, 1997). Almost 60 percent of the sampled households report that an adult male is primarily responsible for grocery shopping; whereas in 22.7 percent of households it is a female and in 5.2 percent of households any member is responsible for grocery shopping. Some households in India follow strict vegetarian diets for cultural/religious reasons; such families do not consume any type of meat, fish, and eggs, which is likely to influence their nutritional consumption. In our sample, about 10 percent of households are vegetarians.

4.3.5. Statistical analysis

We apply a multivariate model framework to investigate factors influencing the adequacy of household nutrient consumption, i.e. HNAR. Hereby, HNARs for calories, proteins, and fats ($k = (c, p, f)$) represent different measures for macronutrient consumption (Y_{macro}) and HNARs for vitamin A, iron, and zinc ($k = (v, i, z)$) for micronutrient consumption (Y_{micro}), respectively. Applying multivariate regressions with a joint estimator allows us to estimate the effects of covariates on the different HNARs simultaneously and we cannot only evaluate the effects of covariates on the consumption of individual nutrients but consumption of overall macro- and micronutrients. To meet model requirements of multivariate normal distributions, we log-transformed all HNARs and estimated the following model specifications with predictor η:

$$ln(Y_{macro}) = \eta_{macro} + \varepsilon_{macro} \Leftrightarrow Y_{macro} = e^{\eta_{macro} + \varepsilon_{macro}} \qquad (4.1)$$

$$ln(Y_{micro}) = \eta_{micro} + \varepsilon_{micro} \Leftrightarrow Y_{micro} = e^{\eta_{micro}+\varepsilon_{micro}} \qquad (4.2)$$

With

$$\eta_k = \beta_{0,k} + \gamma_k I + \gamma_k^{\times} I^{\times} + \beta_{Dist,k} D + \beta_{Dist,k}^{\times} D^{\times} + \gamma_k^{\times\times}(I^{\times} \times D) + \beta_{control} X_{control} \qquad (4.3)$$

Here, Y_{macro} and Y_{micro} are matrices of HNARs-vectors of macro- and micronutrients k, respectively. The stochastic error terms, ε, are assumed to be $\varepsilon \sim (0_k, \Sigma)$ with Σ being the variance-covariance matrix. The predictor η contains a constant $\beta_{0,k}$ and parameters γ, β_{Dist}, and $\beta_{control}$ representing fixed effects of variables in matrices I, D, and $X_{control}$. Matrix I contains the vectors of categorical variables for different types of agricultural operations and off-farm employment ($I = (i_{agriculture}, i_{off-farm})'$) and matrix D two vectors of distances to Bangalore and the closest towns to village centers ($D = (x_{dist\_Bangalore}, x_{dist\_Town})'$). The control variables presented in section 3.4 are included in $X_{control}$.

Another key element of our analysis is the interaction terms, $I^{\times} = (i_{agriculture} \times i_{off-farm})$ to capture the effects of different combinations of agricultural operations and off-farm employment on HNARs. Furthermore, we want to understand how households' location and the resulting access to markets affect their nutrition consumption. Therefore, we also consider the effects of interaction terms $D^{\times} = (x_{dist\_Bangalore} \times x_{dist\_Towns})$ to obtain a more flexible measure of households' locations in the rural-urban interface. Finally, we allow for interaction between $I^{\times}$ and either of the distance measures, $(I^{\times} \times D) = (i_{agriculture} \times i_{off-farm} \times x_{dist\_Bangalore/Towns})$.[18] An introduction to multivariate regression models and more information on inference can be found in Anderson (1984).

4.4 Results and Discussion

4.4.1. Descriptive analysis

In Tables 4.3 and 4.4, we present the means of all six log-transformed HNARs grouped by different agricultural operations and off-farm employment. Tests for overall mean differences and t-test to evaluate differences between particular groups give a first idea of interactions between the employment choice and HNARs. A mean value larger than 0 ($ln(1) = 0$), implies an above RDA consumption for the respective nutrient (compare Table 1).

For agricultural operations (Table 4.3), we find significant mean differences in three out of the six nutrients, namely calorie, iron, and zinc. Households with non-commercialized agriculture appear to

[18] Including interaction effects with all four variables did not add any more information to the model and inference becomes increasingly complex. Thus, we only consider either distance in the interaction term.

have significantly higher HNARs for these three nutrients than the households with no agriculture. Note that the difference for iron HNAR crosses the adequacy recommendation with no agriculture households having lower (<0 mean values) and non-commercialized households having higher (>0 mean values) than the RDA for iron. A similar pattern is observed for the difference between no agriculture households and households with commercialized agriculture, though the magnitude of the differences is not as big as for non-commercialized and no agriculture households. Out of the remaining nutrients, only HNAR for vitamin A does not show any significant differences between the different farm activities. For protein and fat, non-commercialized households have significantly higher HNAR than no agriculture households and commercialized households.

Table 4.3. Average HNARs for all the six nutrients by agricultural operations

	Mean differences	**t-tests**					
		Non-commercialized	$\overleftrightarrow{a}$	Commercialized	$\overleftrightarrow{b}$	No agriculture	$\overleftrightarrow{c}$
Ln(HNARs)							
Calories	**	0.285		0.240	*	0.195	***
Protein		0.325	*	0.266		0.247	**
Fat		0.891	*	0.802		0.817	*
Vitamin A		-0.531		-0.529		-0.456	
Iron	***	0.067		0.028	***	-0.092	***
Zinc	***	0.288		0.251	***	0.169	***

Note: ***p<0.01, **p<0.05, *p<0.1. $\overleftrightarrow{a}$ – difference between non-commercialized and commercialized agriculture; $\overleftrightarrow{b}$ – difference between commercialized and no agriculture; $\overleftrightarrow{c}$ – difference between no agriculture and non-commercialized agriculture.

The same exercise with off-farm employment shows significant mean differences for all nutrients (Table 4.4). The pattern of significant differences between individual groups is more homogenous than in Table 4.3; households with no off-farm employment have significantly higher HNARs for all nutrients than households with at least one member working in permanent off-farm employment. Again, the difference in HNAR for iron crosses zero (>0 mean values). For HNAR of calories, we also observe a significant difference between households with casual and households without any off-farm employment.

Table 4.4. Average HNARs for all the six nutrients by off-farm employment

	Mean differences	**t-tests**					
		No off-farm	$\overleftrightarrow{a}$	Permanent	$\overleftrightarrow{b}$	Casual	$\overleftrightarrow{c}$
<u>Ln(HNARs)</u>							
Calories	***	0.336	***	0.176		0.255	*
Protein	***	0.357	***	0.225		0.294	
Fat	***	0.917	***	0.781		0.829	
Vitamin A	*	-0.454	**	-0.533		-0.422	
Iron	***	0.079	***	-0.061		0.029	
Zinc	***	0.320	***	0.175		0.269	

Note: ***p<0.01, **p<0.05, *p<0.1. $\overleftrightarrow{a}$ – difference between no off-farm and permanent off-farm employment; $\overleftrightarrow{b}$ – difference between permanent and casual off-farm employment; $\overleftrightarrow{c}$ – difference between casual and no off-farm employment.

4.4.2. Multivariate regression

A table that depicts all of the possible interaction effects for all macro- and micronutrients in our model (equation (4.3)) would be very complex. To ease interpretation, we present the results for the interaction terms in cross-tables and only display statistically significant estimates. The two important aspects of our conceptual framework (section 4.2) – the full composite effect of employment choices and market access on HNARs – are presented in Table 5 and Table 6, respectively. Full estimation results can be found in Appendix 4.2 and Appendix 4.3. Because the dependent variables are log-transformed, the coefficients are given in percentage changes. Note that the reference groups for the estimated effects of agricultural operations and off-farm employment are non-commercialized agriculture and no off-farm employment, respectively (gray column and row in Tables 4.5 and 4.6). Hence, the estimated effects have to be understood relative to the mean HNARs of these reference groups. In section 4.4.1 (Tables 4.3 and 4.4), we show that these groups have the highest average HNARs for calories, proteins, fats, iron, and zinc; whereas, they have the lowest HNAR for vitamin A. We chose these reference groups because we consider non-commercialized agriculture to be the traditional livelihood strategy of smallholder households.

Table 4.5. Cross-table – (Interaction) effects of different employment choices as percentage change on HNARs (based on parameter estimates γ_k and $\gamma_k^{\times}$ in equation (4.3))

	No interaction		Agricultural operations				
			Non-Commercialized	Commercialized		No agriculture	
	Macro	Micro		Macro	Micro	Macro	Micro
Off-farm employment *No interaction*	*Not applicable*			C: - P: -27.8* F: -30.7*	V: - I: -36.6** Z: -34.0**	-	-
No off-farm							
Permanent	-	-		C: - P: 50.2’ F: -	V: - I: 94.9** Z: 59.9*	-	-
Casual	C: - P: - F: -83.8*	-		C: - P: - F: 722.6**	-	C: - P: - F: 313’	-

Note: ***p<0.01, **p<0.05, *p<0.1. ’ indicates significance levels with 0.1<p-values>2.0. - indicates that coefficients are not statistically significant. HNARs: C=Calories, P=Proteins, F=Fats, V=Vitamin A, I=Iron, Z=Zinc.

Controls include household size, caste, asset index, a dummy variable for dairy production dummy, gender of household head, age of household head, literacy of household head, a dummy variable for vegetarian diet, supermarket food purchases, person purchasing the food, and transect dummy

Compared with a non-commercialized agricultural household, a household with commercialized agriculture but no off-farm employment consumes 28 to 37 percent lower levels of proteins, fats, iron, and zinc. Considering the above-RDA HNARs for these nutrients, it appears that households that generate their income through commercialized agriculture display less excess nutrient consumption than non-commercialized agricultural households. This might be associated with an initially positive income effect, which exhibits a shift away from the consumption of energy-dense staples to a diversified diet (Cazzuffi et al., 2020; Ntakyo and van den Berg, 2019; Pingali and Khwaja, 2004). However, if we look at households that obtain income from both commercialized agriculture and permanent off-farm employment, we see a different picture. These households consume between 22 (-27.8+50.2=22.4) and 59 (-36.6+94.9) percent more macro- and micronutrients. This might be explained by a larger share of food purchased in markets when the share of household labor assigned to income-generating agricultural operations and off-farm employment increases. Furthermore, if some household members work outside the farm, they might bring changes in lifestyle and food preferences. Though some forms of lifestyle changes are beneficial if they lead to healthy eating practices (Popkin, 1999), in the case of Bangalore it seems that the effect of off-farm employment rather contributes to unhealthy eating patterns and overnutrition. This shows that considering the full composite effect (main and interaction effect) of different income-generating employment choices is important for household nutrition. Previous studies that considered only either the agricultural operations or off-farm employment dimension might, thus, provide partial evidence on the relationship between livelihood strategies and nutrition (Carletto et al., 2017; Rahman and Mishra, 2019; Sibhatu et al., 2015).

We also find some interesting results for the fat consumption of households pursuing casual off-farm employment. If a non-commercialized household adds casual off-farm employment to its livelihood portfolio, its fat consumption reduces by over 83 percent compared with a household with no off-farm employment. Nonetheless, when a household engages in both commercialized agriculture and casual off-farm employment, the fat consumption is almost 640 percent higher. Note, however, that this estimate is based on only a very small group of observations (Table 4.2).

In Figure 4.4, we showed that employment choices seem to be clustered in space and depend on access to agricultural and labor markets. In Appenidx 4.4 and Appendix 4.5, we present simple graphs plotting HNARs against distance to Bangalore and the closest town, respectively. It appears that there are slight gradients; these relationships are, however, not statistically significant in the regression analysis (Table 4.6).

Table 4.6. Cross-table – (Interaction) effects of different employment choices and distance to closest town as percentage changes on HNARs (based on parameter estimates $\boldsymbol{\gamma_k^{\times\times}}$ equation (4.3))

	Distance to closest town			Agricultural operations			
			Non-Commercialized	Commercialized		Non-farm	
	Macro	Micro		Macro	Micro	Macro	Micro
Off-farm employment							
Distance to closest town	-	-		C: - P: 2.7’ F: -	V: - I: 3.2’ Z: 3.0*	-	-
No off-farm							
Permanent	-	-		C: - P: -3.3’ F: -3.9’	V: -4.1’ I: -5.1* Z: -3.5’	-	-

Casual	C: - P: - F: 16.9*	-		C: -8.8’ P: - F: -16.4*	-	-	-

Note: ***p<0.01, **p<0.05, *p<0.1. ’ indicates significance levels with 0.1<p-values>2.0. - indicates that coefficients are not statistically significant. HNARs: C=Calories, P=Proteins, F=Fats, V=Vitamin A, I=Iron, Z=Zinc.

Controls include household size, caste, asset index, a dummy variable for dairy production dummy, gender of household head, age of household head, literacy of household head, a dummy variable for vegetarian diet, supermarket food purchases, person purchasing the food, and transect dummy

Interestingly, it is the same agricultural operations and off-farm employment, and their interactions that have significant effects on HANRs in Table 4.5 show significant associations with market access (i.e., distance to the closest town). A smallholder household with commercialized agriculture but no off-farm employment consumes around 3 percent more macro- and micronutrients with every kilometer away from the closest town. Thus, the negative effect we see for commercialized agricultural operation in Table 4.5 depends on where a household is located. That is, the households with commercialized agricultural display an increased excess consumption of nutrients if they are located far away from urban centers and food markets. Again, similar to the observation in Table 4.5, the effect changes for the households receiving income from commercialized agriculture and permanent off-farm employment. That is, households with this combination of income-generating employment choices exhibit less overnutrition if they are located further away from the closest town.

It appears that there are distinct differences in nutrient consumption levels of households pursuing income-generating agricultural operations and off-farm employment, and their combinations, at least in our study area. Non-commercialized households that switch to a commercialized agricultural operation seem to improve their nutritional status by consuming less excess nutrients. However, if these households are located further away from an urban center they display an increase in excess consumption of nutrients. It might be that these households in the hinterland are stuck in traditional dietary patterns consisting of staple foods than the ones that are closer to a town and, thus, display excess consumption of nutrients (likely similar to non-commercialized households). In contrast, households with commercialized agriculture and permanent off-farm employment seem to have completely different consumption patterns. Households with this combination of employment choices consume excess nutrients, thus, more likely to be prone to overnutrition. Furthermore, this association weakens for households in the hinterlands than the ones closer to a town. This may be due to an unhealthy lifestyle or a larger share of income to be spent in food markets to buy energy-dense food items among households located closer to a town. A similar pattern for obesity prevalence in India is shown by Aiyar et al. (2021). Thus, our results show that a simple linear relationship between income generated by different employment choices and nutrition is unlikely. Rather there seems to be a threshold, until which income generated by employment choices supports improvement in nutrition (by consuming less excess nutrients), and beyond which additional income contributes to further overconsumption of macro- and micronutrients.

Table 4.7. Effects of control variables as percentage changes on HNARs

Variables	**Percentage change in HNARs**					
	Macronutrients			**Micronutrients**		
	Calories	**Protein**	**Fat**	**Vitamin A**	**Iron**	**Zinc**
Dairy production	7.8**	6.2*	12.8**	2.7	8.8**	8.3**
(Dummy – Yes)	(0.028)	(0.088)	(0.007)	(0.573)	(0.036)	(0.025)
Number of household	-6.2***	-6.0***	-6.6***	-8.2***	-7.7***	-6.9***
members	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Gender of household head	-3.8	-1.7	-5.1	-7.5	-4.2	-3.4
(Dummy – Female)	(0.249)	(0.631)	(0.233)	(0.102)	(0.278)	(0.327)
Age (years)	0.0	-0.2**	0.0	-0.1	0.1	-0.1
	(0.930)	(0.030)	(0.779)	(0.635)	(0.340)	(0.645)
Literacy of household	-1.8	-1.3	0.2	2.1	-1.8	-2.1
head (Dummy -Yes)	(0.572)	(0.694)	(0.965)	(0.648)	(0.638)	(0.528)
Caste (ref. General)						
SC&ST	-5.3	-4.7	-7.7*	-4.3	-4.4	-4.4
	(0.101)	(0.161)	(0.066)	(0.350)	(0.248)	(0.199)
OBC	-0.6	-1.6	-1.1	-1.9	-1.3	-2.4
	(0.845)	(0.616)	(0.798)	(0.669)	(0.730)	(0.463)
Ration card (ref. None)						
APL	4.5	1.9	5.6	2.9	0.4	3.6
	(0.535)	(0.802)	(0.560)	(0.777)	(0.965)	(0.639)
BPL	3.4	1.5	-3.2	-10.9*	3.0	5.4
	(0.464)	(0.758)	(0.588)	(0.076)	(0.584)	(0.271)
Asset index (count)	1.9**	2.7**	4.9***	5.1***	2.2**	2.2**
	(0.034)	(0.004)	(<0.001)	(<0.001)	(0.034)	(0.017)
Main grocery shopper (ref. Adult female)						
Adult male	3.7	3.6	4.0	2.5	7.1*	3.8
	(0.296)	(0.323)	(0.386)	(0.612)	(0.092)	(0.304)
Others	2.7	2.7	0.7	-4.8	4.6	2.8
	(0.532)	(0.540)	(0.897)	(0.405)	(0.367)	(0.525)
Vegetarian diet	8.4*	1.7	8.0	11.1*	5.8	4.9
(Dummy – Yes)	(0.077)	(0.715)	(0.195)	(0.099)	(0.289)	(0.310)

Transect	-2.9	-4.7	-6.7*	-7.7*	0.8	-3.2
(Dummy – South)	(0.359)	(0.144)	(0.093)	(0.071)	(0.829)	(0.318)
Intercept	107.3**	138.2**	180.4**	30.9	48.3	110.3**
	(0.011)	(0.004)	(0.006)	(0.503)	(0.239)	(0.013)

Note: ***p<0.01, **p<0.05, *p<0.1. p-values in parentheses.

One important exception in our study is vitamin A, which, on average, is under-consumed and does not show any statistically significant interaction with employment choices (Tables 4.5 and 4.6). Vitamin A shows some individual patterns in the estimation results for the control variables (Table 4.7). For example, dairy production significantly increases the HNARs of both macro- and micronutrients, except vitamin A. Besides, vitamin A is the only nutrient that yields an almost statistically significant and negative effect for female lead households. Also, BPL ration card holders consume significantly less vitamin A. Since these are both common signs of low wealth, we can conclude that the only form of undernutrition in our sample prevails mainly in socio-economically disadvantaged households. The only positive effect on vitamin A consumption is reported for a vegetarian diet.

Next to vitamin-A-specific effects, households with more members have statistically significant lower HNARs for all the six nutrients implying that household size reduces the individual nutrient uptake. The same holds for the number of assets a household owns, which increases HNARs for all six nutrients. Assets are generally considered as wealth indicators. Since the largest positive effect of assets (5.1 percent) is observed for vitamin A, this fits our previous findings that socio-economic characteristics of the household play a significant role in vitamin A undernutrition.

4.5. Conclusions

We analyze how different employment choices of smallholder households affect their food security. We are particularly interested in how the different combinations between household agricultural operations and off-farm employment are associated with nutrition, an aspect that has so far been neglected in the literature. Especially, when urbanization and improved market access enable households to engage in more than one form of employment, it is not just different types of employment chosen but also their combinations that affect their nutrition. Therefore, we present a conceptual framework describing the pathways between household employment choice and nutrition while accounting for the composite effect of different agricultural operations and off-farm employment, and the market access on the production and consumption side. In our empirical analysis, we use the HNARs of three macronutrients (calorie, protein, and fat) and three micronutrients (vitamin A, iron, and zinc) to explore these interactions between employment choices and household nutrition in the rural-urban interface of Bangalore. For all nutrients, except for vitamin A, we find that the average HNARs are above the recommended levels of consumption. Such high HNARs for macronutrients (especially for calories and fat) show the onset of dietary transition among our sample households and suggest the existence of multiple forms of malnutrition.

There are three main results of our regression analysis. First, a mix of income-generating agricultural operations and off-farm employment in households' livelihood portfolio is associated with changes in HNARs, and, second, this association depends on the distance to the closest town. Relative to non-commercialized agriculture, households with commercialized agriculture but no off-farm employment display an improvement in their nutritional status by consuming less excess nutrients. Furthermore, we can see an increase in the excess nutrient consumption if these commercialized households are located in the hinterlands than the households with similar employment choices but located closer to a town. Proximity to an urban center improves market access on both the production and consumption side, which might lead to a shift away from energy-dense staples to a diversified diet and thus, less excess nutrient consumption (Pingali, 2007b; Pingali and Sunder, 2017). In contrast, if households earn income from commercialized agriculture and permanent off-farm employment, the outcome is the overconsumption of nutrients. This effect, again, is less prominent among households in the hinterlands than the ones with a similar livelihood portfolio located closer to a town. Thus, we find a distinct difference between nutrition patterns among different employment choices. Factors driving these differences are probably the share of income generated from agricultural commercialization and off-farm employment relative to own agricultural production, and access to food outlets but also lifestyle changes due to urban proximity and off-farm opportunities. Besides, the relationship between income generated from employment choices and nutrition appears to be non-linear. This means we have a positive nutritional outcome up to a certain threshold and beyond which there is an onset of overnutrition.

Third, vitamin A, a seriously lacking nutrient in the diet of our average sample households is not significantly influenced by different livelihood strategies and market access. However, there are signs that vitamin A undernutrition is associated with household socio-economic characteristics (such as asset index, type of ration card, and female household head). Thus, socio-economically disadvantaged households suffer most from this deficiency. Besides, a vegetarian diet improves vitamin A consumption.

These results not only fill an important gap in the literature but are also relevant for policymakers. We show that agricultural operations and off-farm employment, when considered as a single dimension show less excess nutrient consumption, however, combinations between them are mainly associated with excess consumption of nutrients. Thus, initiatives targeting the food systems to prevent emerging health issues such as overweight and/or non-communicable diseases should consider the full livelihood portfolio of a household. Especially, households active in commercialized agriculture and with members engaged in off-farm employment are vulnerable to overconsumption of nutrients. Strengthening market access on the production and consumption side is one of the commonly advocated policy measures to improve nutrition in smallholder households. Such policies have to account for the negative health effects that pose in terms of access to unhealthy dietary patterns, especially, in those areas facing multiple burdens of malnutrition. We also show that the undernutrition of vitamin A in our study is rather linked to socio-economic factors and not to employment choices. Thus, to fight severe undernutrition it is important to support disadvantaged families (e.g. female-headed households or families or families under the poverty line).

The framework we propose in the study can be further applied in regions experiencing malnutrition as well as urbanization and rural transformation. Future research can aim to derive causal effects using panel data and relevant methods. One possible extension would be to differentiate between skilled and unskilled laborers to further explore the relevance of lifestyle changes associated with off-farm employment and (over) nutrition. Furthermore, it is also worth exploring the role of dairy farming (for own consumption and selling in the market) in household nutrition. Since our nutrition indicators are estimated at the household level, we can draw no conclusions about the intra-household distribution of nutrients, especially the nutrient intake by vulnerable household members such as children and women. Therefore, another extension would be to use individual intake data to apply this conceptual framework.

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Appendix

Appendix 4.1. Summary statistics of sample households

Variables		Obs.	Mean	St. Dev.	Median
Distance to Bangalore	From village centers to Bangalore city center in kilometers	941	27.546	9.793	26.795
Distance to closest town	From village centers to the center of closest town (incl. Bangalore) in kilometers; see Fig. 2	941	11.479	3.414	11.031
Controls					
Dairy production	Dummy variable; 1=household is active in dairy production	941	0.538		
Household members	Number of household members (count)	941	4.624	2.113	4
Gender of the household head	Dummy variable; 1=male household head	941	0.777		
Age	Age of household head in years	941	47.083	13.664	45
Literacy of household head	Dummy variable; 1=household head can read	941	0.665		
Caste	***General***	941	0.470		
	SC&ST		0.269		
	OBC		0.261		
Ration card	Factor variable; Ration card held by the household	941			
	None		0.095		
	APL		0.052		
	BPL		0.853		
Asset index	Number of durable assets owned by the household (count)	941	5.750	1.698	6
Main grocery shopper	Factor variable; Household member normally purchasing food items in the market	941			
	Female		0.227		
	Male		0.595		
	Others		0.178		
Vegetarian diet	Dummy variable; 1=household follows a vegetarian diet	941	0.097		
Transect	Dummy variable; 1=Southern transect	941	0.454		

Appendix 4.2. Association between employment choices and HNARs of macronutrients – multivariate regression results

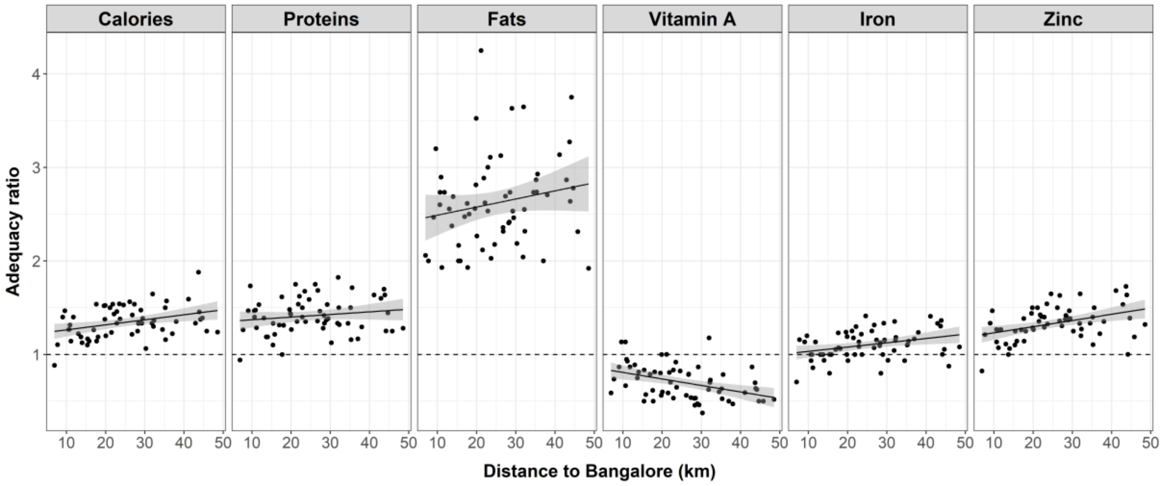
	% change in HNARs		
Variables	**Calories**	**Protein**	**Fat**
Agricultural operations (ref. non-commercialized)			
Commercialized	**-27.8** (0.092)	**-30.7** (0.070)	-26.4 (0.225)
No agriculture	17.6 (0.589)	13.8 (0.680)	38.8 (0.404)
Off-farm employment (ref. no off-farm)			
Permanent	-15.5 (0.433)	-20.0 (0.319)	-23.6 (0.337)
Casual	-54.0 (0.274)	-28.0 (0.657)	**-83.8** (0.050)
Agricultural operations × Off-farm employment			
Commercialized × Permanent	33.8 (0.265)	***50.2*** (0.136)	52.8 (0.215)
Commercialized × Casual	160.1 (0.207)	66.9 (0.517)	**722.6** (0.033)
No agriculture × Permanent	-26.8 (0.365)	-17.6 (0.589)	-24.8 (0.526)
No agriculture × Casual	72.2 (0.485)	11.5 (0.894)	***313.0*** (0.164)
Distance to Bangalore (km)	-0.5 (0.511)	-0.6 (0.396)	0.3 (0.712)
Distance to closest town (DCT) (km)	-0.9 (0.676)	-1.2 (0.607)	1.8 (0.528)
Distance to Bangalore × Distance to closest town	0.0 (0.938)	0.0 (0.754)	***-0.1*** (0.191)
Agricultural operations × Distance to closest town			
Commercialized × Distance to closest town	*2.4* (0.158)	*2.7* (0.134)	2.0 (0.363)
No agriculture × Distance to closest town	-1.9 (0.453)	-1.9 (0.470)	-3.0 (0.350)
Off-farm employment × Distance to closest town			
Permanent × Distance to closest town	0.6 (0.748)	1.1 (0.577)	1.8 (0.459)
Casual × Distance to closest town	7.8 (0.260)	3.9 (0.580)	**16.9** (0.073)
Agricultural operations × Off-farm employment × Distance to closest town			
Commercialized × Permanent × Distance to closest town	-2.4 (0.273)	***-3.3*** (0.152)	***-3.9*** (0.179)
Commercialized × Casual × Distance to closest town	***-8.8*** (0.191)	-5.2 (0.469)	**-16.4** (0.051)
No agriculture × Permanent × Distance to closest town	2.4 (0.414)	1.8 (0.549)	1.8 (0.631)
No agriculture × Casual × Distance to closest town	-5.8 (0.408)	-2.0 (0.787)	-11.3 (0.205)

Note: p-values in parentheses. Bold coefficients indicate significance levels with p-values<0.1. Bold and italic coefficients indicate significance levels with 0.1≤ p-values>0.2.

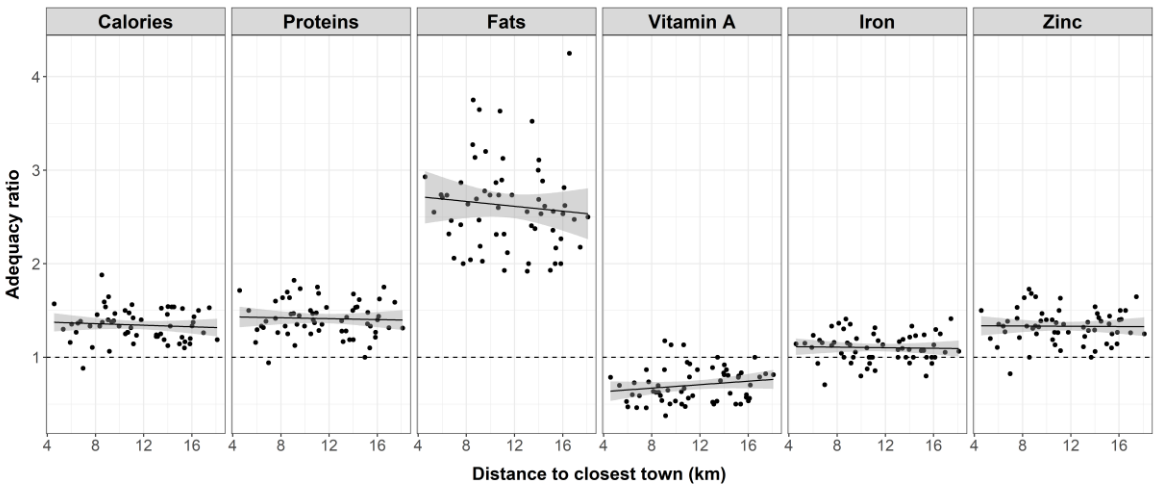
Appendix 4.3. Association between employment choices and HNARs of micronutrients – multivariate regression results

	% change in HNARs		
Variables	**Vitamin A**	**Iron**	**Zinc**
Agricultural operations (ref. non-commercialized)			
Commercialized	-21.8 (0.368)	**-36.6** (0.045)	**-34.0** (0.040)
No agriculture	36.4 (0.463)	12.9 (0.731)	4.4 (0.890)
Off-farm employment (ref. no off-farm)			
Permanent	-19.3 (0.479)	***-27.9*** (0.195)	-23.9 (0.224)
Casual	65.9 (0.613)	-56.8 (0.314)	-44.7 (0.425)
Agricultural operations × Off-farm employment			
Commercialized × Permanent	54.9 (0.235)	**94.9** (0.030)	**59.9** (0.086)
Commercialized × Casual	-3.9 (0.970)	***221.2*** (0.202)	102.2 (0.374)
No agriculture × Permanent	-28.5 (0.489)	-16.2 (0.662)	-12.5 (0.771)
No agriculture × Casual	-46.4 (0.570)	59.8 (0.608)	37.9 (0.693)
Distance to Bangalore (km)	***-1.6*** (0.113)	**-0.4** (00652)	-0.4 (0.616)
Distance to closest town (DCT) (km)	-1.2 (0.690)	-1.0 (0.684)	-1.3 (0.551)
Distance to Bangalore × Distance to closest town	0.1 (0.562)	0.0 (0.782)	0.0 (0.834)
Agricultural operations × Distance to closest town			
Commercialized × Distance to closest town	2.3 (0.335)	***3.2*** (0.106)	**3.0** (0.089)
No agriculture × Distance to closest town	-2.0 (0.561)	-2.2 (0.458)	-1.3 (0.627)
Off-farm employment × Distance to closest town			
Permanent × Distance to closest town	1.7 (0.520)	2.3 (0.299)	1.5 (0.428)
Casual × Distance to closest town	-0.8 (0.928)	7.6 (0.351)	6.8 (0.344)
Agricultural operations × Off-farm employment × Distance to closest town			
Commercialized × Permanent × Distance to closest town	***-4.1*** (0.184)	**-5.1** (0.048)	***-3.5*** (0.126)
Commercialized × Casual × Distance to closest town	-2.1 (0.830)	-8.7 (0.272)	-6.9 (0.334)
No agriculture × Permanent × Distance to closest town	1.5 (0.707)	1.3 (0.695)	1.2 (0.690)
No agriculture × Casual × Distance to closest town	1.3 (0.896)	-4.0 (0.631)	-4.3 (0.559)

Note: p-values in parentheses. Bold coefficients indicate significance levels with p-values<0.1. Bold and italic coefficients indicate significance levels with 0.1≤ p-values>0.2.



Appenidx 4.4. Association between village HNARs and distance to Bangalore (gray areas represent 90 % confidence intervals for the trend lines)



Appenidx 4.5. Association between village HNARs and distance to the closest town (gray areas represent 90 % confidence intervals for the trend lines)

5. Conclusions

Considering the rural-urban interface of Bangalore as a setting, this dissertation studies the individual nutritional status and household nutrient consumption in the face of rapid urbanization. For this, two objectives were stated at the beginning of this dissertation (Chapter 1). The first objective was to estimate how the consumption of a diversified diet and energy-dense processed foods is associated with the nutritional status of individuals. The second objective was to estimate how different livelihood strategies and the interactions between them are associated with household nutrient consumption adequacy. These two objectives of the dissertation were studied in three essays that are presented in Chapters 2, 3, and 4. Based on the empirical estimations using the socio-economic survey data from the rural-urban interface of Bangalore, the findings, limitations, and scopes for future research are discussed for each essay in the current chapter.

Essay 1: A quantile regression analysis of dietary diversity and anthropometric outcomes among children and women in the rural-urban interface of India.

Essay 1 (Chapter 2) estimates whether the increased dietary diversity (DD) is associated with improved anthropometric outcomes among children and women. This relationship was estimated not just at mean but also at different points of the conditional distribution of anthropometric outcomes using the quantile regression (QR) method. Six different measures of DD at the individual- and household-level were considered to check whether the estimated associations depend on the DD measure used. There are three findings of this essay. First, increased DD is associated with adverse anthropometric outcomes among overweight/obese children (that is for the children in the upper quantiles of weight-based anthropometric outcomes). Second, except for these, no other associations at any other quantiles for any anthropometric outcomes of children and women are consistently significant for different measures of DD used in the study. Third, estimating the relationship between DD and anthropometric outcomes at the mean obscure variations in this relationship for different subsets of the population, especially in the context of malnutrition.

The findings of this essay indicate that there is no strong and monotonous relationship between DD and anthropometric outcomes in the rural-urban interface of Bangalore. This could be because a diversified diet might be accompanied by a higher intake of energy-dense food items thus leading to an imbalance in macronutrient intake. In such cases, increased DD might not be associated with significant improvements in anthropometric outcomes or even have an adverse association with anthropometric outcomes of overnourished individuals, as the results of this study suggest. Thus, policies designed to improve DD will not be effective in improving (most) anthropometric outcomes across age and gender groups in this setting. Sensitivity of the results to different measures of DD used in this study suggests that, as also highlighted by Miller et al. (2020), the currently used measures of

DD in the literature might have limited validity in assessing multiple burdens of malnutrition. Considering the rapid urbanization and the rising prevalence of malnutrition in many low- and middle-income countries (LMICs), a universal policy of increasing DD might not be effective to prevent malnutrition.

There are a few limitations of this study. The first is that the estimations are explorative and do not produce the causal relationship between DD and anthropometric outcomes. Future research can account for this by using panel data to address the possible endogeneity bias posed by the unobserved factors that affect both DD and anthropometric outcomes. Second, the data do not allow accounting for the intra-year seasonal variation in DD and its implications for anthropometric outcomes. Despite these limitations, the outcomes of this study highlight the need for further research to gather evidence on the validity of DD in explaining improvement in malnutrition. The first step towards this would be to use complementary metrics of DD, which can be constructed with similar data but differ in the depth of information they measure, to understand the relationship between DD and anthropometric outcomes in different contexts. Following this, future research can also aim to devise a DD index that not only implies higher micronutrient intake but also accounts for the negative effects of higher intake of energy, fat, sodium, etc. Some of the initiatives such as the global nutrition monitoring framework include DD as one of the key indicators to measure the six global nutrition targets that are to be achieved by 2025 (WHO, 2017). In those regions facing multiple burdens of malnutrition, the existing measures of DD might not be effective to assess the progress made to achieve these targets. This calls for care while designing and assessing the progress of policies and thus a need for designing improved measures.

This essay is currently under revise and resubmit status in *Food Policy*. The reviewers make two important comments that are worth discussing here. First, one of the reviewers suggests that the literature explaining the relationship between DD and anthropometric outcomes is more clear than what we present it to be in this essay. The comment particularly refers to the recent study by Li et al. (2020), which employs recent demographic and health surveys (DHS) from 35 LMICs to assess the relative significance of factors associated with anthropometric outcomes of children and finds DD as the fifth risk factor across different contexts. Even though DD is an essential factor for improved anthropometric outcomes, the heterogeneities in this relationship (for different age groups and location of residence) found in several empirical studies discussed in section 2.1 (Chapter 2) cannot be ignored. In the context of dietary transition and multiple burdens of malnutrition, increased DD might always not be associated with improved anthropometric outcomes. This is also highlighted by a systematic review and meta-analysis by Salehi-Abargouei et al. (2016), which shows that there is no significant association between DD and obesity. Furthermore, in the rural-urban interface setting in addition to increased DD individuals might also consume excess quantities of calories and fat. In this case, the marginal increase in DD might not have significant associations with anthropometric outcomes; even if there is, it might be different for undernourished and overnourished individuals. The existing heterogeneities in the relationship between DD and anthropometric outcomes and the limited validity of DD in explaining multiple burdens of malnutrition highlight the need for estimating this relationship for different sub-sets of population. This brings to the second important comment by the reviewers. That is to provide a discussion on whether there is additional merit in estimating this relationship using the QR method as opposed to the mean regression method, especially when most of the results indicate insignificant associations. QR method is a useful tool in a setting where obesity is a major challenge. In the context of the rural-urban interface of Bangalore, where this essay has been set, there is 13, 15, and 36 percent of overweight/obesity among younger children, older children, and women, respectively. Thus, there is a need to strengthen the argument to use the QR method from the perspective of existing multiple burdens of malnutrition in the context of the rural-urban interface. These two major comments from the reviewers will be addressed by providing an improved discussion on the relative contribution of this essay to the literature and strengthening the discussion of results. Accounting for these comments would bring a few modifications to the introduction and discussion sections of Chapter 2.

Essay 2: Processed food consumption and peri-urban obesity in India.

Essay 2 (Chapter 3) estimates how the consumption of calories from semi- and ultra-processed foods is associated with the rising prevalence of obesity among women. This essay produces three findings on the relationship between processed foods and obesity in the Indian rural-urban interface. First, excess consumption of semi-processed food calories is significantly associated with the increasing prevalence of obesity. This association is prominent among lower-income groups and households that acquire subsidized semi-processed foods from the public distribution system (PDS). Calories from ultra-processed foods are associated with the prevalence of obesity among the higher-income groups. Second, there is a threshold, in the form of an individual's ability to meet their recommended dietary allowances (RDA) for calories, beyond which the calories from semi-processed foods are associated with the increasing prevalence of obesity. Third, in line with the broader literature, the relationship between semi-processed foods and obesity becomes weaker for the women who engage in relatively labor-intensive activities. The results also indicate that there are lifestyle change effects on obesity through the off-farm employment characteristic of the household and this effect is further moderated by the education of women.

These findings provide important insights on the role of dietary transition in the rising prevalence of obesity in India. At the early to middle stage of structural transformation (ST) (as observed in India), it is important to account for the level of industrial food processing to understand the diet correlates of obesity. This is because semi-processed foods are widely consumed in everyday diets in India and are considered luxury goods. Thus, any improvement in the economic condition increases the consumption of semi-processed foods, especially for lower-income groups. The ease of their access and affordability over time in India (through PDS and food markets) has further facilitated their excess consumption. Thus, even in the presence of ultra-processed foods, the calories from semi-processed foods pose a greater risk for the prevalence of obesity, especially for lower-income groups. However, among higher-income groups, similar to the evidence from high-income countries, calories from ultra-processed foods drive the risks for the increasing prevalence of obesity. This might be because the individuals in higher-income groups can afford to buy ultra-processed foods at market prices. They might also face a higher opportunity cost of cooking food at home and the ultra-processed foods help to reduce the time spent on cooking. Since the improvements in the socioeconomic status of people seem to drive the excess consumption of semi- and ultra-processed foods and thus, obesity; it is important to design interventions to increase awareness about healthy diet and lifestyle habits. Furthermore, the threshold effects observed for semi-processed foods show that they only become associated with obesity once the women meet their RDA for calories. This suggests that providing nutrition information on weight management and calorie consumption at the early stages of ST may be a key strategy to prevent obesity from reaching lower-income groups.

There are two limitations identified for this study that can be addressed by future research. First, it is possible that the variables measuring processed foods and obesity might not be exogeneous. There can be a potential reverse causality between processed foods and obesity. Increased processed food consumption might increase obesity prevalence but an obese individual is likely to consume more processed foods due to certain hormonal influences. To address such endogeneity bias one would have to use panel data or valid instruments. Since we only have cross-section data at the moment, we tried to address endogeneity bias with the instrumental variable (IV) regression method using the few relevant instruments that we could create from our data set. They are the mean share of expenditure made on processed foods in a village and the percentage of households in a village who eat their meals outside the home. The tests for the endogeneity of regressors fail to reject the null hypothesis that the variables on the share of calories from semi- and ultra-processed foods are exogeneous. Thus, these estimations are provided as an appendix document in chapter 3. Future research can try to address this limitation by using strong instruments (such as distance to the nearest supermarket) and/or by using panel data. Second, calories from the semi- and ultra-processed foods are estimated at the household level and thus, no conclusions can be drawn on the intra-household distribution of calories and their implications on the relationship between processed foods and obesity. However, the results of this study even at the household level show interesting patterns in the role of dietary transition in obesity in India. Future research can extend this estimation by using the individual intake of processed food.

Future research can also extend to study the effect of semi- and ultra-processed foods on non-communicable diseases (NCDs) in India.

Essay 3: You eat what you work – livelihood strategies and nutrition in the Indian rural-urban interface.

Essay 3 (Chapter 4) estimates the full composite effect of different agricultural operations and off-farm employment on households' nutrient consumption adequacy. There are three main findings of this essay. First, different combinations of the two livelihood dimensions – agricultural operations and off-farm employment – are important for households' nutrient consumption adequacy. Of importance is the combination of commercialized agriculture and permanent off-farm employment. The households engaging in such a combination of livelihood strategies display an excess consumption of nutrients. Second, the effect of the aforementioned combination of livelihood strategies decreases for households located further away from the closest small town. That is, households engaged in commercialized agriculture and off-farm employment display less excess consumption of nutrients if they are located further away from the closest town. Third, the results indicate that the relationship between income generated through agriculture and off-farm employment and nutrition is likely to be non-linear. That is, initially an increase in income is associated with improvements in nutrient consumption adequacy, however, further increase in income is associated with overnutrition. Besides, undernutrition is most prevalent among socio-economically disadvantaged households.

The findings of this essay help to bridge the gap in the literature discussing the relationship between household livelihood strategies and nutrition. That is, the full composite of different livelihood strategies should be considered to understand how different agricultural operations and off-farm employment affect nutrition, especially in the context of urbanization. Income generated from different livelihood strategies might often not lead to improvement in nutrition but bring overconsumption of certain nutrients, which increases the prevalence of overnutrition. Thus, interventions targeting food systems to prevent malnutrition should account for the positive as well as the negative effects that different livelihood strategies simultaneously have on household nutrition. Strengthening market access on the production and consumption side is one of the widely advocated policies to improve smallholder nutrition in LMICs. These policies have to account for the negative health effects that market access brings in the form of unhealthy eating practices. The results also show that socio-economically disadvantaged households are the ones prone to severe undernutrition in this rural-urban interface of Bangalore. This calls for the double-duty action framework for nutrition policies in India to fight undernutrition as well as overnutrition (Hawkes et al., 2020).

This essay is explorative but the proposed conceptual framework can be applied in the regions facing malnutrition, dietary transition, urbanization, and rural transformation to gather more evidence on the full composite effect of livelihood strategies on nutrition. There is also a scope to examine how different combinations of livelihood portfolios such as crop-dairy, crop-off-farm, and crop-dairy-off-farm are resilient in the face of rapid dietary transition and malnutrition in LMICs. One possible extension for future research is to differentiate between skilled and unskilled labor to explore the effect of lifestyle changes that accompany off-farm employment on household nutrition.

Key messages of the dissertation

This dissertation highlights three key messages on nutrition in the Indian rural-urban interface. First, to understand the intricate relationship between diets and nutritional status in the rural-urban interface, it is necessary to go beyond the mean analysis and estimate how the relationship between the two differs for different subsets of the population (e.g. undernourished vs. overnourished, calorie adequate vs. calorie inadequate, lower-income group vs. higher-income group, etc.). Second, to understand complex interlinkages between household livelihood characteristics and nutrition, it is an important account for the trade-offs in decision-making on both the production and consumption side. Third, interventions targeting to improve nutritional status in the rural-urban interface should follow a double-duty policy action framework to address multiple burdens of malnutrition.

Reflections

The nutrition situation in India is widely discussed as a puzzle. That is, despite the increase in real income and no long-term increase in the relative food prices, a declining trend in the average calorie intake is observed in India (Deaton and Drèze, 2009). A large part of the literature discusses patterns in calorie intake using cross-sectional and longitudinal data and attributes the calorie intake puzzle to the improved health environment, changing occupational patterns that require lower calories due to lower physical activity levels, non-food expenditures, changing lifestyles, etc. (Basole and Basu, 2015; Deaton and Drèze, 2009; Siddiqui et al., 2019). Despite these improvements, undernutrition remains a major health challenge in India. One of the limitations for estimating the interrelations between declining calorie intake and slow improvements in the anthropometric outcomes was the lack of individual- and household-level data that collects information on both food intake and anthropometric measurements. Thus, the main objective of the FOR2432 (sub-project C05 on patterns and determinants of nutrition and food security in the rural-urban interface) was to study the factors associated with food insecurity (decline in calorie intake) and nutritional status (specifically undernutrition) in the face of rapid urbanization using comprehensive data on household and individual food consumption and anthropometric measurements. The prevalence of overnutrition, as an emerging nutrition-related challenge in the rural-urban interface of Bangalore, was identified during the data exploration. Even though the survey instrument was designed mainly for understanding the factors influencing food insecurity (measured through qualitative as well as quantitative techniques) and undernutrition, detailed household and individual food consumption and anthropometric measurements were helpful to study factors associated with undernutrition as well as overnutrition in this dissertation.

The three essays presented in this dissertation explores the effect of different factors such as processed foods, supermarket purchases, occupation transitions, income, and proximity to the urban centers on nutrition in the rural-urban interface. However, despite accounting for this set of comprehensive factors, there arises a question of what changes or additions would have been made to the survey design or instruments had I/we knew the extent and severity of ongoing dietary and nutrition transition in Bangalore. If I could design and conduct the survey all over again, I would have made the following changes to the survey instrument or collect additional information on the following variables. First, I would have collected the household food consumption expenditure data for a recall period of seven days. Though a 14-day recall data accounts for variations in the food consumption for a longer period there is a higher possibility of recall bias. A 7-day recall food consumption data allows for constructing most DD indicators and provides a good measure of nutrient availability/consumption at the household level. Second, in addition to the anthropometric measurements such as weight and height, I would have also taken the measurements of waist and hip circumference. The BMI outcomes along with the waist-to-hip ratio help to measure obesity and central obesity in individuals. This would have helped to better understand the severity of nutrition transition and the resulting prospects for the incidence of NCDs in the rural-urban interface of Bangalore. In addition, I would have taken the anthropometric measurements of the child's father as this variable is found to be an important correlate of growth among children in recent studies. Finally, some of the estimations in this dissertation are an attempt to account for the effect of physical activity levels and lifestyle changes through the proxy variables such as occupation, off-farm employment, and education. However, these variables are only rough proxies and might not account for the actual effects of physical activity and lifestyle changes on nutrition. Provided that the conditions allow, I would have included a section on nutritional knowledge, physical activities, alcohol consumption, smoking behavior, and lifestyle changes to understand how these influence the prevalence of overnutrition and NCDs in the rural-urban interfaces.

If the conditions in the near future allow, some of the suggestions made for the changes/additions can be incorporated for the survey instrument in the upcoming blood test survey in phase II of the FOR2432 research unit. Using this new data set, there is a scope to extend some of the essays presented in this dissertation by applying panel data estimation methods.

Way forward

Indian ST is different from other emerging countries in Asia and Latin America because much of the increase in urbanization and economic growth is found to be the outcome of the emergence of small towns rather than big cities. If the urbanization patterns in these small towns follow similar patterns that are explained for the mega-city of Bangalore, it is likely that the nutrition and health of people in peripheries of the small towns might also be similarly affected by the urban environment of the region. Thus, to understand the factors driving the nutrition transition in India, it is useful to extend some of the concepts studied in this dissertation for the rural-urban interface of Bangalore to the national level data. Furthermore, by applying advanced methods of analyzing the spatial data, one can estimate how proximity to urban centers (mega-city and small towns) influence these relationships. It would also be interesting to study the nutritional condition at the peripheries of rapidly urbanizing cities in other LMICs, that are at different stages of ST, to understand the factors and determinants of food consumption and nutritional status of millions of people who live in the rural-urban interfaces.

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List of Publications

Discussion/working papers:

Purushotham, A., Mittal, N., Ashwini, B.C., Umesh, K.B., von Cramon-Taubadel, S., & Vollmer, S. (2018). Dietary diversity and child anthropometric outcomes: a quantile regression analysis. *Courant Research Centre 'Poverty, Equity and Growth' Discussion Paper 259, University of Göttingne.*

Purushotham, A., Aiyar, A., & von Cramon-Taubadel, S. (2021) Dietary transition and its relationship with socio-economic status and peri-urban obesity. '*Department für Agrarökonomie und Rurale Entwicklung' Discussion Paper 2104, University of Göttingen.*

Papers under review in peer-reviewed journals:

Purushotham, A., Mittal, N., Ashwini, B.C., Umesh, K.B., von Cramon-Taubadel, S., & Vollmer, S. "A quantile regression analysis of dietary diversity and anthropometric outcomes among children and women in the rural-urban interface of India". Submitted and under revision and resubmission in *Food Policy*.

Purushotham, A., & Steinhübel, L. "You eat what you work – livelihood strategies and nutrition in the rural-urban interface". Submitted and under review in *World Development*.

Papers ready to submit to the peer-reviewed journals:

Purushotham, A., Aiyar, A., & von Cramon-Taubadel, S. "Processed food consumption and peri-urban obesity in India".

Conference presentations:

Purushotham, A. et al. (2018). Dietary diversity and children anthropometric outcomes: a quantile regression analysis. *14th Annual Conference on Economic Growth and Development*, 19 – 21 December 2018, New Delhi, India.

Purushotham, A. (2019). Socio-economic correlates of nutrient consumption and dietary quality in the rural-urban interface of Bangalore. *8th European Association of Agricultural Economics Ph.D. Workshop*, 10 – 12 June 2019, Uppsala, Sweden.

Declaration of own contribution

I declare my contribution to the three essays presented in this dissertation.

The first essay "A quantile regression analysis of dietary diversity and anthropometric outcomes among children and women in the rural-urban interface of India" is written in collaboration with Nitya Mittal, B.C. Ashwini, K.B. Umesh, Stephan von Cramon-Taubadel, and Sebastian Vollmer. I participated in the data collection with B.C. Ashwini and other graduate students from the research unit FOR2432. I was responsible for developing the research question, data curation, performing statistical analysis, interpreting results, and writing the paper with Nitya Mittal. K.B. Umesh, Stephan von Cramon-Taubadel, and Sebastian Vollmer critically reviewed the paper and contributed to the submitted version of the paper.

The second essay "Processed food consumption and peri-urban obesity in India" is the result of collaboration with Anaka Aiyar and Stephan von Cramon-Taubadel. For this paper, I participated in the data collection with other graduate students of the research unit FOR2432. The conceptualization of research questions was done in collaboration with Anaka Aiyar and Stephan von Cramon-Taubadel. I was responsible for data curation, statistical analysis, and writing the preliminary draft of the paper. Interpretation of results and editing and writing the submitted version of the paper was done in collaboration with Anaka Aiyar and Stephan von Cramon-Taubadel.

The third essay "You eat what you work – livelihood strategies and nutrition in the rural-urban interface is written in collaboration with Linda Steinhübel. I participated in data collection with Linda Steinhübel and other graduate students of the research unit FOR2432. I was responsible for conceptualization, statistical analysis, and writing the paper in collaboration with Linda Steinhübel. I was responsible for data curation and Linda Steinhübel was responsible for the methodology part. In addition, Prof. Dr. Stephan von Cramon-Taubadel provided useful comments for the final draft of the paper.

The data used in this dissertation is compiled within the research unit FOR2432 – "Social-ecological systems in the Indian rural-urban interface: Functions, scales, and dynamics of transition" and is funded by the German Research Foundation (DFG).

Affidavit

I hereby declare on oath that:

1. This work has not already been submitted in the same or a similar form to other examination offices.

2. I have not applied for a doctoral degree at any other university.

Göttingen, May 27, 2021.

(Signature)

I hereby declare on oath that this dissertation was written independently and without undue assistance.

Göttingen, May 27, 2021.

(Signature)