

Courant Research Centre

‘Poverty, Equity and Growth in Developing and Transition Countries: Statistical Methods and Empirical Analysis’

Georg-August-Universität Göttingen
(founded in 1737)



Discussion Papers

No. 259

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

**Anjali Purushotham, Nitya Mittal, B.C. Ashwini, K.B. Umesh,
Stephan von Cramon-Taubadel and Sebastian Vollmer**

**First Version: September 2018
This Version: September 2021**

Platz der Göttinger Sieben 5 · 37073 Goettingen · Germany
Phone: +49-(0)551-3921660 · Fax: +49-(0)551-3914059

Email: crc-peg@uni-goettingen.de Web: <http://www.uni-goettingen.de/crc-peg>

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

Anjali Purushotham^{a,*}, Nitya Mittal^b, B.C. Ashwini^c, K.B. Umesh^c, Stephan von Cramon-Taubadel^a,
Sebastian Vollmer^b

^a *Department of Agricultural Economics and Rural Development, University of Göttingen, Germany*

^b *Department of Economics and Centre for Modern Indian Studies, University of Göttingen, Germany*

^c *Department of Agricultural Economics, University of Agricultural Sciences, Bangalore, India*

* Corresponding author E-mail address: akatiga@gwdg.de

Abstract

Based on a primary survey conducted in the rural-urban interface of Bangalore, this study contributes to the understanding of the relationship between dietary diversity (DD) and anthropometric outcomes of young children (6 months – 5 years) (measured by weight-for-age (WAZ), weight-for-height (WHZ) and height-for-age (HAZ) z-scores), school-aged children (6 – 14 years) (measured by Body Mass Index (BMI) z-scores and HAZ scores) and women (15 years and above) (measured by BMI). 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 the metric used. Our results show that increased DD is associated with higher z-scores at the lower quantiles of the WAZ distribution. In addition, we find a positive association between DD and upper quantiles of WHZ and BMI z-scores of young and school-aged children, respectively. This reflects an adverse effect of increased DD on anthropometric outcomes among overweight/obese children. Except for these, no other associations at any other quantile for any anthropometric outcome of young children, school-aged children, and women are consistently significant for various measures of DD. Our results suggest that policies that focus on improving DD might not be effective in improving (most) anthropometric outcomes especially in areas facing multiple burdens of malnutrition.

Keywords: Dietary diversity, Anthropometric outcomes, Quantile regression, India, Urbanization, Rural-urban interface

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 (Cawley, 2015; Hoddinott et al., 2008; Victora et al., 2008). In addition, adolescence is a critical period that may provide a window of opportunity to redress nutritional deficits accumulated during early childhood and provide resources needed for adult life (Patton et al., 2016; Prentice et al., 2013). Among women, malnutrition is associated with morbidity and mortality in the next generation (Patton et al., 2016). Though reductions in the prevalence of undernutrition among children in India have been observed in the past decades, the rates are still high (NFHS-4, 2015-16). At the same time, India is now facing issues of overnutrition (NFHS-4, 2015-16). The prevalence of overweight among women has doubled over the last decade.

Among various factors that contribute to better nutritional status, nutritious food is considered to play an important role. Higher dietary diversity (DD) is widely advocated by many studies as a means to improve nutritional status (Agrawal et al., 2019; Aiyar et al., 2021; Corsi et al., 2016; Gausman et al., 2018; Kim et al., 2017; Pingali et al., 2017). Improved/higher DD as a means to improve anthropometric outcomes is emphasized by (WHO, 2020) and (UNICEF, 2018). ***Poshan Abhiyan***, 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).

However, policies that focus on DD are not unanimously supported by evidence from the empirical literature. Several studies examine the relationship between DD and anthropometric failure/undernutrition for young children and women. While some studies find that increasing DD is associated with improvements in anthropometric outcomes, the results vary considerably across different age groups and locations of residence (Amugsi et al., 2014; Arimond and Ruel, 2002; Darapheak et al., 2013; Frempong and Annim, 2017; Hatløy et al., 2000; Kheirouri and Alizadeh, 2021; Perkins et al., 2018; Rah et al., 2010; Saaka and Osman, 2013). In addition, many studies do not find any significant relationship between DD and anthropometric outcomes (Heemann et al., 2021; McDonald et al., 2015; Savy et al., 2008). In a recent study, Li et al. (2020) examine the relationship

between anthropometric failure and DD for 35 LMICs. While DD was found to be an important correlate of growth failure, the study also shows that the nature of the relationship is not universal, odds ratios vary from 0.6 in Swaziland to 2.1 in Ethiopia. Similar ambiguities are also observed when one considers overnutrition or overweight/obesity prevalence (Abris et al., 2018; Asghari et al., 2017; Azadbakht and Esmailzadeh, 2011; Oliveira Otto et al., 2018; Salehi-Abargouei et al., 2016).

When framing nutrition policies for India it is imperative to consider the evidence for the Indian population. Most studies find that increasing DD is associated with a lower prevalence of undernutrition among children (Borkotoky et al., 2018; Chandrasekhar et al., 2017; Corsi et al., 2016; Kim et al., 2017; Menon et al., 2015; Meshram et al., 2019). However, Kim et al. (2019) and Li et al. (2020) use the most recently available national data (NFHS-4 2015-16) and find a weak association between DD and anthropometric failure. Moreover, literature for other age groups is scant. Nithya and Bhavani (2016) and Nithya and Bhavani (2018) do not find any significant association for school-aged children and adolescents, but the latter study does find a positive relationship between DD and BMI of women. However, this does not necessarily mean improved nutritional status as higher BMI can be an indicator of overnutrition. Young et al. (2020) show that higher DD is associated with reduced odds of underweight and increased odds of overweight/obesity among adolescent girls and women in India.

The primary objective of this study is to estimate whether increased DD is associated with improvements in anthropometric outcomes for three demographic groups (young children, school-aged children, and adult women). We use the quantile regression (QR) method to examine whether the relationship between DD and anthropometric outcomes varies along the distribution. This allows us to examine the importance of DD for both undernutrition and overnutrition. To our knowledge, there are very few papers that investigate heterogeneity in the association between DD and anthropometric outcomes (Amugsi et al., 2017; Amugsi et al., 2016).

Our study makes two additional contributions. First, it is carried out in a unique setting that has received little consideration not only in India but globally – the rural-urban interface (RUI). 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, due to the rapid urbanization which is often non-linear, messy, and hidden

in many low- and middle-income countries (LMICs) including India (Cohen, 2006; Denis et al., 2012; Ellis and Roberts, 2015), the dynamics of the urban environment spill over the formal boundaries of mega-cities creating interface regions between rural and urban areas. These interface regions span from the outer peripheries of urban cities to traditionally defined rural areas.¹

Second, there are at least 31 different specifications for DD measures that have been used in the literature for studying DD among individuals and households (Marshall et al., 2014). Thus, the ambiguity observed in the relationship between DD and anthropometric outcomes might be due in part by the use of different DD indicators. Our extensive dataset allows us to use several different measures of DD to examine whether the relationship between DD and anthropometric outcomes is sensitive to the choice of DD measure.

2. Study area, sampling, and data description

2.1. Rural-urban interface of Bangalore

Bangalore is a rapidly growing mega-city in the southern state of Karnataka (India). Bangalore's population was 9.6 million according to 2011 census data and is expected to more than double by 2031 (Bharadwaj, 2017). Over the last six decades, the size of Bangalore city has increased over ten times, from 69 sq. km to 741 sq. km (Sudhira et al., 2007). Population growth, industrial development, rapid growth in the information technology (IT) sector, and infrastructural development in the region have led to rapid urbanization and the geographical expansion of Bangalore city (Varkey, 2018). Over the same period, smaller secondary towns have grown in the vicinity, creating a complex, poly-centric pattern of urbanization surrounding Bangalore (Steinhübel and Cramon-Taubadel, 2020). A dense network of highways connects rural areas, secondary towns, and Bangalore city to one another (Directorate of Census Operations Karnataka, 2011). The resulting RUI outside the boundary of Bangalore city is mainly categorized as rural by definition but it exhibits characteristics that are not typical of traditional

¹ There are studies that estimate the prevalence of DBM (Chagomoka et al., 2016) or pattern of dietary intake (Henjum et al., 2015) in peri-urban areas. However, to the best of our knowledge, no studies investigate the relationship between DD and anthropometric outcomes in this setting.

rural areas. For instance, the distinct livelihood characteristics observed in a traditional rural and/or urban setting might not hold in the RUI. Households in the RUI have access to employment opportunities that are predominant in rural areas such as agriculture and small-scale industries, but also to urban labor markets (Directorate of Census Operations Karnataka, 2011).

Similarly, we observe that households in the RUI of Bangalore have access to a wider range of food items, available through a variety of sources such as own production, mom & pop stores, hypermarkets, and fast-food outlets. All these outlets sell foods ranging from fresh to processed foods. Improved access to diverse food items combined with increased income opportunities can result in dietary transition. Furthermore, improved infrastructure, transport facilities, and access to off-farm employment opportunities can lead to a shift towards a sedentary lifestyle in such regions. These developments suggest that the RUI of Bangalore is exhibiting characteristics of what Popkin (1993) categorizes as the second and third stages of nutrition transition.

A further characteristic of nutrition transition that we observe in the RUI of Bangalore, typical of LMICs, is the double burden of malnutrition (DBM) (Mittal and Vollmer, 2020). Bangalore and surrounding regions face substantial undernutrition alongside a high prevalence of overweight/obesity (NFHS-5, 2019-20). About a quarter of children are underweight in both rural and urban Bangalore and not much improvement has been made between 2015-16 and 2019-2020. Although the prevalence of overweight/obesity is lower (4-6 percent) (NFHS-5, 2019-20), overweight/obesity rates have increased by over 50 percent in rural Bangalore in the past 4 years. Among adult women, the prevalence of undernutrition is low (10-14 percent) but the rates of overweight/obesity have increased rapidly to 33-40 percent (NFHS-5, 2019-20). The complexities observed in dietary patterns and nutritional outcomes in the RUI of Bangalore are not unique to this area, but also likely to be observed in other fast-urbanizing areas in India and elsewhere (Hawkes et al., 2017).

2.2. Sampling design

This study is based on a primary socio-economic survey conducted between December 2016 and May 2017. Our research area is set in two transects in the RUI of Bangalore, one extending towards the north,

and the other extending towards the southwest part (two polygons in Figure 1) of Bangalore city. A two-stage stratified random sampling design was used to select the sample households. We created a Survey Stratification Index (SSI), which is a composite index constructed using the distance to the Bangalore city center and the building density (Hoffmann et al., 2017). In the first stage, the transects were divided into three strata each (rural, peri-urban, and urban), based on terciles of the SSI. Then, we randomly selected villages from each stratum using probability proportional to the size and selected 61 sample villages. Finally, using village household lists, sample households were randomly selected, proportional to the size of the village. The final sample consists of 1275 households. This survey is part of a larger German-Indian collaborative project on the socio-ecological implications of urban expansion, FOR2432.

For each sample household, the main decision-maker was interviewed to collect the socio-demographic information of the household. In addition, the primary caregiver of the household was interviewed to collect information on household food consumption for the past 14 days. Furthermore, individual 24-hour dietary recall data were collected for all three demographics considered in the study. Here, the adult women provided information about their own dietary intake, while for children (both young and school-aged) the information was provided by their mothers. Height and weight were measured for all children aged 6 months to 5 years, children from 6 to 14 years, and all women aged 15 years and above in the household. Participation was voluntary, and written consent was obtained before the interview and anthropometric measurements took place.

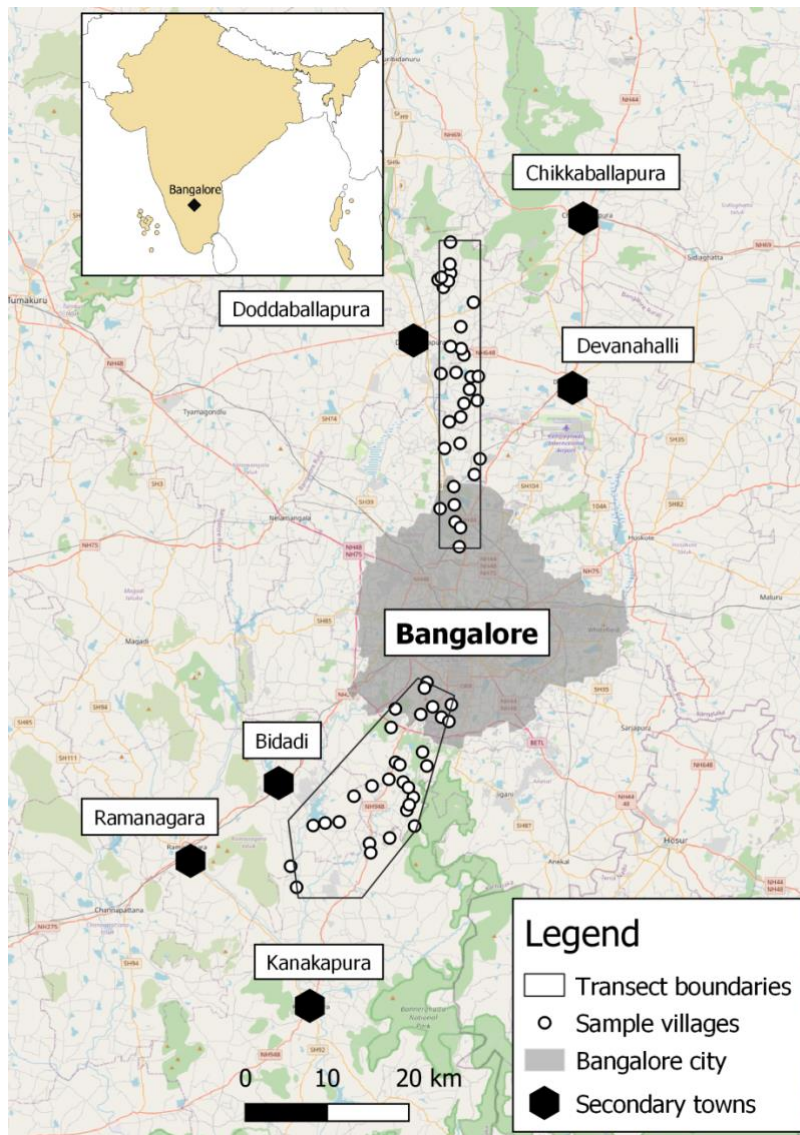


Figure 1. Study area, research transects, and sample villages

2.3. Variable definition

Our rich dataset provides information on anthropometric outcomes of young children (aged 6 months – 5 years); school-aged children (6 – 14 years); and women (15 years and above). Using the anthropometric measurements, we calculate weight-for-age (WAZ), weight-for-height (WHZ), and height-for-age (HAZ) z-scores for young children, body mass index (BMI) z-scores and HAZ scores for school-aged 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 (McDonald et al., 2015; Saaka and Osman, 2013). One of the reasons for this is that it is easier to collect information

at the household level, especially in settings in which it is difficult to interview primary caregivers. However, the intra-household distribution of resources is not always equitable (Gupta et al., 2020), and anthropometric outcomes are ultimately affected by individual intakes. We, therefore, construct both household- and individual-level DD measures to evaluate if the ambiguous results in the literature are driven by this difference in measuring DD (Table 1). 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 are constructed by a simple count of different food groups consumed. Household Dietary Diversity Score (H-DDS), constructed using 14-day food consumption data, is based on 12 food groups (Kennedy et al., 2011). At the individual level, DDS is constructed using 24-hour dietary recall data. All food items are divided into 8 groups for both young children (Swindale and Bilinsky, 2006), and for women (Kennedy et al., 2011). These 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 school-aged children, we use the same food groups as in H-DDS to construct a DDS for them. We call this School-aged children's Dietary Diversity Score (SDDS).

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 for all three demographic groups. Household food consumption data allows us to calculate two additional measures – **Household Food Consumption Score (H-FCS)** and **Household Mean Micronutrient Adequacy Ratio (H-MMAR)**. While DDS 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 (INDEX Project, 2018b). MMAR is the average of adequacy ratios for ten micronutrients (calcium, iron, vitamin A, vitamin B6, vitamin C, zinc, thiamin, riboflavin, niacin, and folate) (INDEX Project, 2018a). To summarize, we use two individual-level and four household-level DD measures, as outlined in Table 1.

Table 1. Description of different dietary diversity measures used in the study

Dietary diversity indicator	Target group	Description	Range
Children's dietary diversity score (CDDS)	Young children (6 months – 5 years)	Constructed using 24-hour dietary recall data for young children. <i>It consists of eight food groups – grains, roots, and tubers; vitamin A rich plant foods; other fruits and vegetables; meat, poultry, fish, seafood; eggs; pulses/legumes/nuts; milk and milk products; and foods cooked in oil/fat.</i>	0-8
School-aged children's Dietary Diversity Score (SDDS)	School-aged children (6 – 14 years)	Constructed using 24-hour dietary recall data for school-aged children. <i>It consists of 12 food groups – cereals; white tubers and roots; legumes, nuts, and seeds; vegetables; fruits; meat; eggs; fish and fish products; milk and milk products; sweets and sugars; oils and fats; and spices, condiments, and beverages.</i>	0-12
Women's dietary diversity score (WDDS)	Women (15 years and above)	Constructed using 24-hour dietary recall data for women. <i>It consists of eight food groups – starchy staples; dark green leafy vegetables; other vitamin A rich fruits and vegetables; other fruits and vegetables; meat and fish; eggs; legumes, nuts, and seeds; and milk and milk products.¹</i>	0-8
Individual food variety score (I-FVS)	Young children, school-aged children, and women	Constructed using 24-hour dietary recall data for young children, school-aged children, and women. <i>It is the count of different food items consumed by individual young children, school-aged children, and women.</i>	0-146
Household dietary diversity score (H-DDS)	Household	Constructed using 14-day recall household food consumption data. <i>It consists of 12 food groups – cereals; white tubers and roots; legumes, nuts, and seeds; vegetables; fruits; meat; eggs; fish and fish products; milk and milk products; sweets and sugars; oils and fats; and spices, condiments, and beverages.</i>	0-12
Household food consumption score (H-FCS)	Household	Constructed using 14-day recall household food consumption data. <i>It is the frequency weighted dietary diversity score consisting of the following nine food groups and their weights given in parentheses – main staples (2); pulses (3); vegetables (1); fruit (1); meat and fish (4); milk (4); sugar (0.5); oil (0.5); and condiments (0).</i>	0-112
Household food variety score (H-FVS)	Household	Constructed using 14-day recall household food consumption data. <i>It is the count of different food items consumed by the household.</i>	0-145
Household mean micronutrient adequacy ratio (H-MMAR)	Household	Constructed using 14-day recall household food consumption data. <i>It is the average of the household-level nutrient adequacy ratios for ten micronutrients – iron, zinc, vitamin A, calcium, vitamin B6, vitamin C, thiamin, riboflavin, niacin, and folate.</i>	0-100

Notes:¹ The organ meat group, which is considered in the original construction of WDDS, is omitted here because information on organ meat consumption is not available in our sample

2.4. Missing data

Though repeated visits were made to collect anthropometric data for young children, we were unable to collect information for all members of all sample households. After accounting for outliers and missing data, our sample consists of 214, 202, and 196 observations for young children for WAZ, WHZ, and HAZ, respectively. To ensure that there is no sample selection bias, we compare the characteristics of children with and without complete data using logistic regressions. We find that children with missing data are younger and belong to the Hindu religion. We control for these characteristics in our estimations. After accounting for outliers and missing data, our sample consists of 407 and 405 school-aged children for BMI z-score and HAZ score, respectively. We find that participation in the survey by children in this age group is not significantly related to any socio-economic characteristics. Finally, anthropometric information was available for 67 percent of the surveyed women in the study; after accounting for outliers and missing data, our sample consists of 1332 women. The logistic regression results show that women for whom data are missing are likely to be unmarried, work outside the home in the public or private sector, belong to households with lower family size, belong to Hindu religion, and other caste categories.² We account for these characteristics in our analysis.³

3. Empirical methods

We apply ordinary least squares (OLS) regression and QR methods to estimate the relationship between DD and anthropometric outcomes. We estimate two model specifications. The first includes several control variables. For both young and school-aged children we include the following control variables – (i) child characteristics (age, gender, and education (only for school-aged children)); (ii) maternal characteristics (mother's age, education, and height); and (iii) household characteristics (family size, caste, religion, economic status, a dummy for agricultural activity, and access to sanitation facilities and safe drinking water). For women we include – (i) women characteristics (age, education, occupation, number of children, marital status); and (ii) household characteristics (same as for children). We also

² Results of the missing data analysis are available on request.

³ Our sample for young children is powered to detect an effect size of 0.05 and higher in an OLS model. The samples for school-aged children and women are powered to detect even smaller effect sizes.

control for transect fixed effects. Proximity to an urban center has been found to influence the dietary pattern, lifestyle choices, and nutritional status of an individual (Aiyar et al., 2021; Bren d’Amour et al., 2020). Steinhübel and Cramon-Taubadel (2020) show that the urbanization process is poly-centric, implying that an individual’s choices are affected by proximity to the mega-city but also to nearby secondary towns. For this reason, we control for household distance to Bangalore city center and the closest town in the regression analysis. The estimation equation used for the multivariate QR analysis is therefore as follows:

$$Y_{i,j,v} = \beta_{0,\tau} + \alpha_{\tau} DD_{i,j,v} + \beta_{c,\tau} X_{control_{i,j,v}} + \varepsilon_{i,j,v,\tau} \quad (1)$$

where Y is the anthropometric outcome variable for individual i in household j in village v . α_{τ} is the quantile-specific coefficient of interest that quantifies the association between DD and the respective anthropometric outcome. We examine the relationships at 5th, 10th, 25th, 50th, 75th, 90th, and 95th quantiles of the anthropometric outcome. $X_{control}$ is the vector of control variables.

To help understand whether proximity to an urban center affects the relationship between DD and anthropometric outcomes in this complex setting, we also employ a second model specification that includes interaction between DD measures and distance to the closest town.⁴ The equation for this second specification is as follows:

$$Y_{i,j,v} = \beta_{0,\tau} + \alpha_{\tau} DD_{i,j,v} + \alpha_{\tau}^{\times} (DD_{i,j,v} * Distance\ to\ closest\ town_v) + \beta_{c,\tau} X_{control_{i,j,v}} + \varepsilon_{i,j,v,\tau} \quad (2)$$

where $\alpha_{\tau}^{\times}$ measures the quantile-specific interaction effect between DD and distance to closest town.

We cluster standard errors at the village level in both models.⁵

⁴ We include interaction with the distance to closest town because we expect it will have more direct and strong effect on individual’s choices than the distance to Bangalore city. We also estimate a model with interaction of DD measures with both the distance to closest town and Bangalore city, but the results are similar to model 2 presented in section 5.

⁵ Since, we have missing observations for 26, 32, and 33 percent of young children, school-aged children, and women, respectively, we used the multiple imputation method to impute missing values. The results (available from the authors) based on samples that include imputed values do not change our conclusions.

4. Summary statistics

Table 2 presents the descriptive statistics for young children, school-aged children, and women. Among young children, 28 percent are underweight, 16 percent are wasted, and 36 percent are stunted. In addition, 11 percent are overweight/obese. We observe a similar pattern for school-aged children – 25 percent are underweight whereas 15 percent are overweight/obese. The issue of overweight/obesity is most severe among women. While 35 percent of the women in our sample are overweight/obese, only 16 percent are underweight. This indicates that our sample from the RUI of Bangalore is facing DBM.

The household-level DD measures (last four rows of Table 2) indicate that DD is high in our sample households. For example, households on average consume 10 of the 12 food groups (H-DDS) and meet about 80 percent of their recommended micronutrient requirement (H-MMAR). However, a different picture arises if one considers the individual-level DD measures (rows 7 and 8 of Table 2), which show lower diversity in individual dietary patterns. We do not observe differences in DD among the three demographic groups. The only exception is the higher SDDS for school-aged children, which is driven by a differential classification of food groups for this age group.⁶

⁶ Descriptive statistics for socio-economics characteristics for the three sample demographic groups are available on request.

Table 2. Mean anthropometric outcomes and dietary diversity measures

Variables	Young children (6 months – 5 years)	School-aged children (6 – 14 years)	Women (15 years and above)
Weight-for-age (WAZ)	-1.13 (1.47)		
Height-for-age (HAZ)	-1.27 (1.98)		
Weight-for-height (WHZ)	-0.47 (1.79)		
Body mass index (BMI) scores		-0.85 (1.69)	
Height-for-age (HAZ) scores		-1.26 (1.53)	
BMI			23.34 (4.73)
CDDS/SDDS/WDDS	4.8 (0.80)	7.79 (1.52)	3.65 (0.89)
I-FVS	30.62 (10.99)	30.03 (11.55)	23.57 (10.96)
H-DDS	10.55 (1.12)	10.58 (0.94)	10.40 (1.10)
H-FCS	93.02 (12.01)	91.68 (11.90)	91.28 (13.57)
H-FVS	47.64 (12.66)	48.08 (11.88)	46.18 (12.70)
H-MMAR	80.30 (18.32)	81.86 (15.16)	82.74 (16.39)

Notes: Standard errors in parentheses. CDDS – children’s dietary diversity score; SDDS – school-aged children’s dietary diversity score; WDDS – women’s dietary diversity score; I-FVS – individual food variety score; H-DDS – household dietary diversity score; H-FCS – household food consumption score; H-FVS – household food variety score; H-MMAR – mean micronutrient adequacy ratio.

In Tables 3 to 5, we present the average DD by the nutritional status for each demographic group. Here as well, average individual-level DD measures are lower than the household-level DD measures. Some DD measures indicate that undernourished young children have lower DD than young well-nourished children. However, there is not much statistical difference in average DD by nutritional status for any other group.

Table 3. Dietary diversity measures by the nutritional status of young children (6 months – 5 years)

(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	Underweight	$\vec{a}$	Normal weight			
CDDS	4.76 (0.12)		4.87 (0.05)			
I-FVS	30.13 (1.48)		30.81(0.87)			
H-DDS	10.18 (0.19)	**	10.70 (0.07)			
H-FCS	89.25 (2.04)	**	94.49 (0.78)			
H-FVS	44.58 (1.70)	**	48.84 (0.98)			
H-MMAR	79.80 (2.52)		80.49 (1.44)			
Percentage of children	28		72			
	Wasted	$\vec{a}$	Not-wasted	$\vec{b}$	Overweight/obese	$\vec{c}$
CDDS	4.69 (0.17)		4.87 (0.06)		4.81 (0.12)	
I-FVS	30.21 (1.82)		30.99 (0.94)		28.09 (1.61)	
H-DDS	10.42 (0.31)		10.65 (0.07)		10.40 (0.18)	
H-FCS	91.34 (3.19)		93.58 (0.88)		94.27 (2.21)	
H-FVS	45.96 (2.67)		48.29 (1.03)		48.68 (2.45)	
H-MMAR	78.68 (4.23)		80.45 (1.44)		81.74 (3.17)	
Percentage of children	16		73		11	
	Stunted	$\vec{a}$	Not stunted			
CDDS	4.81 (0.09)		4.84 (0.07)			
I-FVS	28.71 (1.16)		31.11 (0.99)			
H-DDS	10.52 (0.11)		10.63 (0.10)			
H-FCS	92.43 (1.38)		93.84 (1.12)			
H-FVS	45.94 (1.28)	*	48.94 (1.23)			
H-MMAR	80.19 (2.19)		80.07 (1.69)			
Percentage of children	36		64			

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

$\vec{a}$ – statistically significant difference between column (2) and column (4); $\vec{b}$ – difference between column (4) and column (6); $\vec{c}$ – difference between column (6) and column (2).

CDDS – children's dietary diversity score; I-FVS – individual food variety score; H-DDS – household dietary diversity score; H-FCS – household food consumption score; H-FVS – household food variety score; H-MMAR – household mean micronutrient adequacy ratio.

Table 4. Dietary diversity measures by the nutritional status of school-aged children (6 – 14 years)

(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	Underweight	$\vec{a}$	Normal weight	$\vec{b}$	Overweight/obese	$\vec{c}$
SDDS	7.84 (0.13)		7.70 (0.10)	**	8.06 (0.13)	
I-FVS	30.01 (1.03)		29.10 (0.72)	**	33.77 (1.726)	*
H-DDS	10.48 (0.95)		10.66 (0.06)		10.45 (0.12)	
H-FCS	90.62 (1.48)		92.60 (0.64)		89.79 (1.60)	
H-FVS	46.10 (1.23)	*	48.64 (0.73)		49.13 (1.53)	
H-MMAR	80.44 (1.56)		83.27 (0.89)	*	78.59 (2.30)	
Percentage of children	25		60		15	

Variables	Stunted	$\vec{a}$	Not-stunted
SDDS	7.69 (0.12)		7.81 (0.09)
I-FVS	29.52 (1.01)		30.15 (0.69)
H-DDS	10.48 (0.09)		10.62 (0.05)
H-FCS	90.69 (1.18)		91.99 (0.67)
H-FVS	47.36 (1.12)		48.22 (0.69)
H-MMAR	80.09 (1.41)		82.50 (0.88)
Percentage of children	29		71

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

$\vec{a}$ – statistically significant difference between column (2) and column (4); $\vec{b}$ – difference between column (4) and column (6); $\vec{c}$ – difference between column (6) and column (2).

SDDS – school-aged children’s dietary diversity score; I-FVS – individual food variety score; H-DDS – household dietary diversity score; H-FCS – household food consumption score; H-FVS – household food variety score; H-MMAR – household mean micronutrient adequacy ratio.

Table 5. Dietary diversity measures by the nutritional status of women (15 years and above)

(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	Underweight	$\vec{a}$	Normal weight	$\vec{b}$	Overweight/obese	$\vec{c}$
WDDS	3.56 (0.06)	**	3.71 (0.03)	*	3.60 (0.04)	
I-FVS	23.27 (0.76)		23.77 (0.42)		23.42 (0.50)	
H-DDS	10.38 (0.07)		10.38 (0.04)		10.44 (0.04)	
H-FCS	91.13 (0.80)		90.91 (0.55)		91.88 (0.62)	
H-FVS	44.30 (0.83)		45.71 (0.50)	**	47.68 (0.57)	***
H-MMAR	81.57 (1.10)		82.69 (0.65)		83.35 (0.75)	
Percentage of women	16		49		35	

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

$\vec{a}$ – statistically significant difference between column (2) and column (4); $\vec{b}$ – difference between column (4) and column (6); $\vec{c}$ – difference between column (6) and column (2).

WDDS – women’s dietary diversity score; I-FVS – individual food variety score; H-DDS – household dietary diversity score; H-FCS – household food consumption score; H-FVS – household food variety score; H-MMAR – household mean micronutrient adequacy ratio.

5. Results

For each age group and anthropometric outcome, we present OLS and QR results in Tables 6 to 11. For both methods, we estimate two specifications – **model 1** (eq. 1) and **model 2** (eq. 2, which includes interaction with distance to the closest town) – that are presented in **panel A** and **panel B**, respectively.

Young children – WAZ (Table 6)

The OLS results for model 1 (panel A in Table 6) show that there is no significant association between DD measures and WAZ scores at the mean (OLS column). However, QR results show that there is some heterogeneity in this relationship along the WAZ distribution. We find a positive association between DD and WAZ scores at lower quantiles (5th and 10th) of WAZ distribution for some DD measures (some coefficients are significant at 10 percent). In addition, in contrast to no significant association at mean, three of the six measures of DD are significantly and positively associated with WAZ scores at the median (50th quantile). Positive association is also observed at the 75th quantile of WAZ distribution for some DD measures. Children in the lower quantiles are undernourished. Thus, these positive associations at the lower quantiles suggest that increasing DD is associated with higher WAZ scores, indicating improvement in the nutritional status of young children. Furthermore, for some household-level DD measures, increasing DD is negatively associated with WAZ scores at the 90th and 95th quantile. The upper quantile of the WAZ distribution indicates a higher than median weight and is therefore associated with overnutrition. Hence, this result shows that a higher DD is associated with a lower prevalence of overnutrition and better nutritional status. However, an opposite association (positive coefficient) is observed between CDDS and WAZ score at 95th quantile.

In model 2 (panel B of Table 6), we present the results for the interaction effect of distance to the closest town and DD. The OLS results show that increasing H-DDS, on average, is associated with lower WAZ scores for children living away from the closest town. In other words, on average, increasing DD is not associated with improvements in the WAZ scores among children who live farther away from the closest town. However, for this model as well, QR results show some heterogeneities along the distribution. For H-DDS, the negative correlation is driven by upper quantiles only. A similar negative association at

upper quantiles is observed for several other DD measures as well. For some of the measures, the interaction effect has negative coefficient at middle quantiles. While the interaction effects at upper quantiles indicate an improvement in the nutritional status for children living away from the closest town, the opposite is true for middle quantiles.

In summary, even though no significant relationship is observed for DD and WAZ scores at the mean, QR results show some heterogeneities in this relationship. In addition, we also observe that household-level measures of DD are more likely to be significantly associated with WAZ scores than individual-level DD measures.

Young children – WHZ (Table 7)

Similar to WAZ, Panel A of Table 7 suggests that there is no significant relationship between DD and WHZ scores at the mean. However, the QR results reveal some evidence of a positive relationship between DD and WHZ scores at middle (25th to 75th) quantiles for some DD measures (some coefficients are significant at 10 percent). The results for upper quantiles are, however, not consistent. There is a negative coefficient for I- FVS at 90th and 95th quantile. But the coefficients for H-DDS and H-MMAR are positive at 95th quantile, implying that increased DD is associated with higher WHZ scores and a deterioration in nutritional status at these quantiles.

The coefficients on the interaction terms in panel B of Table 7 are mostly negative, implying an inverse relationship between DD and WHZ score as one moves farther away from the town. In other words, for undernourished children (lower quantiles), increasing DD is associated with an improvement in WHZ score among those who live closer to a town. However, among overweight/obese children (upper quantiles), the negative interaction coefficients indicate that higher DD is associated with an increased prevalence of overweight/obesity among children who live closer to a town

Young children – HAZ (Table 8)

OLS results show that there is no significant relationship between DD and HAZ scores at the mean (Panel A of Table 8). However, the QR results show unexpected heterogeneities. For two of the six DD measures, we find that increasing DD is associated with lower HAZ scores at the 95th quantile. Unlike weight-based measures, for HAZ scores a positive association implies improvement in nutritional outcomes throughout the distribution. Thus, the two estimated negative associations at the 95th quantile indicate that higher DD is associated with a lower height.

For model 2 (panel B of Table 8), we focus on the interaction variable between DD and the distance to the closest town. The coefficient on the interaction term is negative between the 50th to 95th quantiles for some measures of DD. This indicates that the adverse relationship between DD and HAZ scores that we discussed in model 1 is stronger among children who live farther from the closest town. The only exception is H-MMAR – for which we find a positive relationship between DD and HAZ scores at mean as well as along the HAZ distribution among children who live farther from the closest town. This could be because of the nature of the construction of H-MMAR, which accounts for the number of important micronutrients consumed in the household.

School-aged children – BMI z-scores (Table 9)

With an exception of I-FVS, OLS results (panel A of Table 9) show no relationship between DD and BMI z-scores. However, QR estimates show significant positive associations at the upper quantiles (90th and 95th) of the BMI z-scores distribution for three of the six DD measures that we consider. This implies that increased DD is associated with an increased prevalence of overweight/obesity among school-aged children. The interaction effects between DD and the distance to the closest town, which are summarized in panel B of Table 9, indicate that the positive association between DD and BMI for school-aged children at the 90th quantile becomes stronger with increasing distance from the closest town.

School-aged children – HAZ scores (Table 10)

Again, we find no significant association at mean from OLS results (panel A, for model 1). Similar to the results found for HAZ scores of young children, here also we find that – for one of the six DD measures considered in the analysis – increased DD is associated with lower HAZ scores at the 75th quantile of HAZ score distribution. Only for H-MMAR do we find positive associations at the upper quantiles (90th and 95th). For model 2 (panel B of Table 10), the interaction coefficient is positive and significant for some measures of DD, mostly at middle and upper quantiles. This implies increasing DD is associated with higher HAZ scores among children who live farther from the closest town.

Women – BMI (Table 11)

As with young and school-aged children, the OLS results for women do not show any significant association between DD and BMI (Table 11 – panel A, OLS column). The QR results for two of the six DD measures show that increased DD is associated with higher BMI at the 5th quantile indicating improvement in the nutritional status of women in this quantile. However, the negative associations between DD and BMI observed at the median quantile (50th) of BMI distribution for two DD measures indicate the deteriorating effect of higher DD on BMI of women. The results presented in panel B of Table 11 show that higher DD is associated with improved nutritional status among women in the lower quantiles (by reducing thinness) and the upper quantile (by reducing overweight/obesity) of the BMI distribution among women who live farther away from the closest town.

An important point to note is that even though we find heterogeneities in the relationships between DD and anthropometric outcomes across the distributions of the outcome variables for all three demographic groups, the estimated coefficients are not consistent across the different DD measures that we consider in the study. Significance levels change, and signs reverse in some cases as well.

Table 6. Relationship between dietary diversity and WAZ scores among young children (6 months – 5 years)

VARIABLES	Panel A – Model 1								Panel B – Model 2							
	OLS	Quantile regression							OLS	Quantile regression						
		5 th	10 th	25 th	50 th	75 th	90 th	95 th		5 th	10 th	25 th	50 th	75 th	90 th	95 th
CDDS	0.168 (0.131)	0.516 (0.349)	0.329 (0.202)	0.237* (0.140)	0.336* (0.202)	0.096 (0.167)	-0.091 (0.316)	0.220*** (0.080)	0.437 (0.512)	-1.208 (1.873)	-0.701 (1.119)	0.049 (0.774)	0.959 (1.022)	0.943 (0.869)	-0.792 (0.703)	0.922 (1.241)
CDDS * Distance to closest town									-0.022 (0.043)	0.158 (0.156)	0.077 (0.096)	0.014 (0.062)	-0.054 (0.087)	-0.063 (0.058)	0.052 (0.045)	-0.048 (0.079)
I-FVS	0.003 (0.009)	-0.031 (0.022)	0.005 (0.017)	0.005 (0.013)	0.013 (0.016)	0.005 (0.015)	-0.007 (0.013)	-0.020 (0.013)	-0.030 (0.031)	-0.199*** (0.041)	-0.121 (0.093)	-0.017 (0.051)	-0.068 (0.043)	-0.041 (0.053)	0.114** (0.053)	0.088 (0.057)
I-FVS * Distance to closest town									0.003 (0.003)	0.015*** (0.004)	0.010 (0.008)	0.002 (0.004)	0.007** (0.003)	0.004 (0.004)	-0.010** (0.004)	-0.009* (0.005)
H-DDS	0.096 (0.105)	0.460** (0.200)	0.319 (0.223)	0.203 (0.178)	0.204** (0.091)	0.226*** (0.070)	-0.372** (0.189)	-0.510* (0.292)	1.147** (0.479)	0.986 (1.261)	0.781 (0.826)	0.752 (0.551)	1.199** (0.526)	1.049** (0.492)	1.263** (0.581)	1.894*** (0.243)
H-DDS * Distance to closest town									-0.094** (0.044)	-0.042 (0.102)	-0.030 (0.063)	-0.052 (0.053)	-0.092** (0.046)	-0.077* (0.046)	-0.157*** (0.054)	-0.203*** (0.034)
H-FCS	0.007 (0.010)	0.034* (0.019)	0.040* (0.023)	0.020 (0.013)	0.022** (0.010)	-0.006 (0.017)	-0.045*** (0.017)	-0.046*** (0.012)	0.063 (0.042)	0.061 (0.099)	-0.071 (0.072)	0.041 (0.094)	0.087 (0.055)	0.110*** (0.041)	0.062 (0.084)	0.038 (0.042)
H-FCS * Distance to closest town									-0.005 (0.004)	-0.002 (0.008)	0.007 (0.006)	-0.002 (0.008)	-0.006 (0.005)	-0.009** (0.004)	-0.008 (0.007)	-0.008* (0.004)
H-FVS	0.006 (0.008)	0.045* (0.025)	0.016 (0.017)	0.008 (0.013)	0.020** (0.010)	0.002 (0.012)	-0.017** (0.009)	-0.025** (0.010)	0.052* (0.027)	0.058 (0.125)	0.038 (0.048)	0.019 (0.039)	0.072** (0.036)	0.030 (0.041)	0.019 (0.050)	0.027 (0.024)
H-FVS * Distance to closest town									-0.004* (0.002)	-0.001 (0.010)	-0.002 (0.005)	-0.001 (0.003)	-0.005 (0.003)	-0.002 (0.003)	-0.002 (0.004)	-0.004* (0.002)
H-MMAR	0.004 (0.006)	0.001 (0.018)	0.001 (0.010)	0.000 (0.009)	0.012 (0.008)	0.016** (0.008)	0.001 (0.011)	-0.009 (0.009)	0.031 (0.024)	-0.007 (0.107)	0.050 (0.045)	0.033 (0.037)	0.064** (0.027)	0.079* (0.047)	-0.005 (0.075)	0.024 (0.056)
H-MMAR * Distance to closest town									-0.002 (0.002)	0.001 (0.009)	-0.005 (0.003)	-0.003 (0.003)	-0.005** (0.002)	-0.007 (0.005)	0.000 (0.006)	-0.003 (0.005)

Notes: Robust standard errors in parentheses. *** p-value<0.01, ** p-value<0.05, * p-value<0.1. Standard errors are clustered at village level. CDDS – children’s dietary diversity score; I-FVS – individual food variety score; H-DDS – household dietary diversity score; H-FCS – household food consumption score; H-FVS – household food variety score; H-MMAR – household mean micronutrient adequacy ratio.

Table 7. Relationship between dietary diversity and WHZ scores among young children (6 months – 5 years)

VARIABLES	Panel A – Model 1								Panel B – Model 2							
	OLS	Quantile regression							OLS	Quantile regression						
		5 th	10 th	25 th	50 th	75 th	90 th	95 th		5 th	10 th	25 th	50 th	75 th	90 th	95 th
CDDS	0.131 (0.157)	0.238 (0.410)	0.211 (0.173)	0.354* (0.184)	0.176 (0.200)	0.085 (0.161)	-0.179 (0.522)	-0.197 (0.453)	0.865 (0.523)	1.937 (2.042)	0.155 (1.333)	0.406 (0.955)	0.718 (0.637)	0.235 (0.869)	0.680 (1.948)	1.743 (1.726)
CDDS * Distance to closest town									-0.059 (0.038)	-0.162 (0.167)	0.006 (0.105)	-0.004 (0.082)	-0.042 (0.052)	-0.011 (0.057)	-0.063 (0.205)	-0.164 (0.139)
I-FVS	-0.013 (0.011)	-0.034 (0.025)	0.007 (0.016)	0.012 (0.015)	-0.003 (0.010)	-0.021 (0.014)	-0.039** (0.016)	-0.083*** (0.015)	-0.049 (0.048)	-0.101 (0.075)	-0.063 (0.053)	-0.025 (0.074)	-0.009 (0.050)	-0.060 (0.111)	-0.145 (0.102)	-0.228*** (0.071)
I-FVS * Distance to closest town									0.003 (0.004)	0.006 (0.007)	0.005 (0.004)	0.003 (0.006)	0.001 (0.004)	0.003 (0.009)	0.008 (0.008)	0.011** (0.006)
H-DDS	0.103 (0.139)	0.216 (0.162)	0.144 (0.161)	0.121 (0.097)	0.043 (0.158)	0.090 (0.259)	0.046 (0.229)	0.555*** (0.068)	0.371 (0.680)	-0.428 (1.070)	0.303 (0.915)	0.065 (0.551)	0.459 (0.768)	0.922 (0.763)	1.835*** (0.641)	2.751*** (0.383)
H-DDS * Distance to closest town									-0.024 (0.061)	0.051 (0.099)	-0.015 (0.085)	0.006 (0.052)	-0.031 (0.056)	-0.085 (0.064)	-0.129** (0.051)	-0.205*** (0.035)
H-FCS	0.013 (0.012)	0.013 (0.022)	0.016 (0.012)	0.019** (0.010)	0.017 (0.014)	0.038*** (0.007)	0.006 (0.018)	-0.000 (0.026)	0.006 (0.057)	0.040 (0.085)	0.034 (0.079)	0.018 (0.053)	0.011 (0.051)	-0.006 (0.072)	0.080 (0.067)	0.007 (0.211)
H-FCS * Distance to closest town									0.001 (0.005)	-0.002 (0.007)	-0.002 (0.006)	0.000 (0.005)	0.001 (0.004)	0.003 (0.006)	-0.005 (0.006)	-0.001 (0.017)
H-FVS	0.006 (0.011)	0.019 (0.023)	0.016 (0.021)	0.016 (0.015)	0.014** (0.007)	0.001 (0.010)	-0.004 (0.026)	-0.001 (0.023)	0.070** (0.034)	0.155* (0.082)	0.083 (0.054)	0.075* (0.043)	0.050** (0.024)	0.073* (0.044)	0.105 (0.077)	0.309*** (0.046)
H-FVS * Distance to closest town									-0.005* (0.003)	-0.013* (0.008)	-0.006 (0.005)	-0.006 (0.004)	-0.004 (0.002)	-0.006* (0.003)	-0.007 (0.006)	-0.022*** (0.003)
H-MMAR	0.007 (0.009)	0.011 (0.016)	0.012 (0.011)	0.009 (0.012)	0.007 (0.013)	0.004 (0.013)	0.004 (0.009)	0.029*** (0.008)	0.118*** (0.036)	0.112* (0.059)	0.096** (0.041)	0.139** (0.057)	0.069 (0.044)	0.150*** (0.044)	0.112* (0.058)	0.149*** (0.033)
H-MMAR * Distance to closest town									-0.010*** (0.003)	-0.009* (0.005)	-0.007** (0.003)	-0.011** (0.005)	-0.006 (0.004)	-0.012*** (0.004)	-0.009* (0.005)	-0.011*** (0.003)

Notes: Robust standard errors in parentheses. *** p-value<0.01, ** p-value<0.05, * p-value<0.1. Standard errors are clustered at village level. CDDS – children’s dietary diversity score; I-FVS – individual food variety score; H-DDS – household dietary diversity score; H-FCS – household food consumption score; H-FVS – household food variety score; H-MMAR – household mean micronutrient adequacy ratio.

Table 8. Relationship between dietary diversity and HAZ scores among young children (6 months – 5 years)

VARIABLES	Panel A – Model 1								Panel B – Model 2							
	OLS	Quantile regression							OLS	Quantile regression						
		5 th	10 th	25 th	50 th	75 th	90 th	95 th		5 th	10 th	25 th	50 th	75 th	90 th	95 th
CDDS	0.062 (0.143)	0.369 (0.540)	0.156 (0.354)	0.010 (0.353)	-0.087 (0.177)	-0.054 (0.119)	-0.226 (0.780)	-0.337 (0.312)	0.699 (0.520)	1.168 (2.436)	-0.430 (0.941)	0.271 (1.293)	1.043 (1.031)	0.419 (0.566)	4.206*** (1.606)	3.983*** (1.054)
CDDS * Distance to closest town									-0.050 (0.041)	-0.059 (0.191)	0.046 (0.083)	-0.021 (0.106)	-0.085 (0.069)	-0.032 (0.040)	-0.340** (0.133)	-0.318*** (0.081)
I-FVS	0.005 (0.013)	0.026 (0.039)	0.021 (0.038)	0.002 (0.021)	0.001 (0.013)	-0.012 (0.012)	0.028* (0.014)	-0.030 (0.020)	0.020 (0.062)	-0.066 (0.099)	-0.033 (0.067)	0.076 (0.069)	0.037 (0.070)	0.016 (0.059)	0.055 (0.084)	0.061 (0.053)
I-FVS * Distance to closest town									-0.001 (0.005)	0.008 (0.008)	0.005 (0.006)	-0.006 (0.005)	-0.003 (0.006)	-0.002 (0.004)	-0.002 (0.007)	-0.006 (0.004)
H-DDS	-0.081 (0.139)	0.326 (0.350)	0.262 (0.485)	0.094 (0.332)	-0.087 (0.128)	-0.161 (0.336)	-0.489* (0.264)	-0.798*** (0.233)	1.207* (0.699)	0.623 (1.092)	0.637 (1.622)	1.675 (1.196)	1.322** (0.623)	1.290 (1.450)	2.117 (1.892)	1.505*** (0.545)
H-DDS * Distance to closest town									-0.116* (0.066)	-0.023 (0.091)	-0.053 (0.133)	-0.136 (0.087)	-0.128** (0.056)	-0.128 (0.126)	-0.226 (0.158)	-0.192*** (0.046)
H-FCS	-0.007 (0.012)	-0.024 (0.031)	-0.007 (0.046)	0.009 (0.027)	-0.006 (0.014)	-0.016 (0.020)	-0.033 (0.026)	-0.016 (0.015)	0.070 (0.055)	0.107 (0.173)	-0.045 (0.100)	0.046 (0.140)	0.077* (0.046)	0.099* (0.055)	0.167** (0.068)	0.191*** (0.035)
H-FCS * Distance to closest town									-0.006 (0.005)	-0.008 (0.013)	0.003 (0.009)	-0.003 (0.012)	-0.007* (0.004)	-0.009* (0.005)	-0.015*** (0.006)	-0.019*** (0.004)
H-FVS	-0.002 (0.011)	0.020 (0.036)	-0.011 (0.026)	0.016 (0.016)	0.009 (0.015)	-0.002 (0.012)	-0.017 (0.026)	-0.038* (0.020)	-0.022 (0.032)	-0.043 (0.072)	-0.017 (0.086)	-0.027 (0.049)	-0.023 (0.042)	-0.033 (0.079)	-0.030 (0.081)	-0.028 (0.085)
H-FVS * Distance to closest town									0.002 (0.003)	0.006 (0.005)	0.001 (0.009)	0.004 (0.003)	0.003 (0.003)	0.002 (0.006)	0.001 (0.005)	-0.001 (0.006)
H-MMAR	-0.001 (0.008)	0.024 (0.020)	0.010 (0.022)	-0.001 (0.009)	-0.002 (0.009)	-0.001 (0.007)	-0.002 (0.013)	-0.004 (0.010)	-0.092** (0.039)	-0.190*** (0.064)	-0.125*** (0.039)	-0.101*** (0.030)	-0.056 (0.040)	-0.046 (0.048)	-0.150* (0.078)	-0.070 (0.055)
H-MMAR * Distance to closest town									0.008** (0.003)	0.016*** (0.006)	0.011*** (0.003)	0.008*** (0.002)	0.005 (0.003)	0.004 (0.004)	0.013* (0.007)	0.007 (0.004)

Notes: Robust standard errors in parentheses. *** p-value<0.01, ** p-value<0.05, * p-value<0.1. Standard errors are clustered at village level. CDDS – children’s dietary diversity score; I-FVS – individual food variety score; H-DDS – household dietary diversity score; H-FCS – household food consumption score; H-FVS – household food variety score; H-MMAR – household mean micronutrient adequacy ratio.

Table 9. Relationship between dietary diversity and BMI z-scores among school-aged children (6 – 14 years)

VARIABLES	Panel A – Model 1								Panel B – Model 2							
	OLS	Quantile regression							OLS	Quantile regression						
		5 th	10 th	25 th	50 th	75 th	90 th	95 th		5 th	10 th	25 th	50 th	75 th	90 th	95 th
SDDS	0.055 (0.061)	-0.077 (0.093)	-0.105 (0.066)	0.031 (0.071)	0.046 (0.066)	0.103 (0.095)	0.202** (0.095)	0.287*** (0.038)	-0.008 (0.177)	0.197 (0.512)	-0.093 (0.210)	-0.070 (0.216)	0.119 (0.174)	0.189 (0.338)	0.170 (0.377)	0.397 (0.263)
SDDS * Distance to closest town									0.005 (0.014)	-0.028 (0.045)	-0.001 (0.019)	0.010 (0.020)	-0.006 (0.014)	-0.009 (0.028)	0.003 (0.035)	-0.010 (0.024)
I-FVS	0.013* (0.008)	0.013 (0.020)	-0.004 (0.023)	0.014 (0.011)	0.016** (0.007)	0.016 (0.013)	0.022** (0.011)	0.037*** (0.009)	-0.011 (0.024)	0.065 (0.071)	0.012 (0.062)	0.004 (0.031)	0.003 (0.022)	0.003 (0.048)	-0.081** (0.038)	-0.018 (0.067)
I-FVS * Distance to closest town									0.002 (0.002)	-0.005 (0.007)	-0.002 (0.006)	0.001 (0.003)	0.001 (0.002)	0.001 (0.004)	0.009*** (0.003)	0.004 (0.005)
H-DDS	0.014 (0.101)	0.046 (0.225)	0.205 (0.159)	0.096 (0.118)	0.060 (0.133)	0.121 (0.141)	-0.148 (0.468)	-0.107 (0.249)	0.294 (0.350)	-0.191 (0.686)	0.028 (0.597)	0.323 (0.331)	0.307 (0.395)	0.505 (0.700)	0.711 (0.749)	0.735 (0.919)
H-DDS * Distance to closest town									-0.024 (0.030)	0.018 (0.058)	0.012 (0.049)	-0.021 (0.029)	-0.021 (0.030)	-0.031 (0.058)	-0.078 (0.066)	-0.068 (0.079)
H-FCS	-0.007 (0.010)	-0.001 (0.018)	0.002 (0.019)	-0.006 (0.013)	-0.011 (0.013)	-0.013 (0.014)	-0.004 (0.014)	-0.005 (0.014)	-0.045 (0.038)	-0.037 (0.049)	-0.069* (0.036)	-0.041 (0.040)	-0.048 (0.082)	-0.071 (0.059)	-0.011 (0.050)	0.040 (0.026)
H-FCS * Distance to closest town									0.003 (0.003)	0.004 (0.004)	0.006** (0.003)	0.003 (0.003)	0.003 (0.006)	0.005 (0.005)	0.001 (0.005)	-0.004 (0.002)
H-FVS	0.009 (0.010)	-0.002 (0.018)	0.002 (0.018)	0.007 (0.015)	0.011 (0.010)	0.014 (0.012)	0.015 (0.020)	0.031** (0.015)	-0.017 (0.026)	0.008 (0.069)	-0.053 (0.051)	-0.015 (0.031)	-0.000 (0.025)	-0.004 (0.038)	-0.084* (0.043)	0.113* (0.058)
H-FVS * Distance to closest town									0.002 (0.002)	-0.001 (0.007)	0.005 (0.004)	0.001 (0.002)	0.001 (0.002)	0.001 (0.003)	0.009** (0.004)	-0.007 (0.005)
H-MMAR	-0.004 (0.006)	-0.007 (0.011)	-0.009 (0.011)	-0.005 (0.006)	-0.003 (0.009)	-0.011 (0.012)	-0.011 (0.008)	-0.006 (0.007)	-0.010 (0.019)	0.010 (0.051)	-0.018 (0.029)	-0.010 (0.016)	0.005 (0.025)	-0.043 (0.030)	-0.033 (0.025)	-0.010 (0.025)
H-MMAR * Distance to closest town									0.001 (0.001)	-0.001 (0.004)	0.001 (0.002)	0.000 (0.001)	-0.001 (0.002)	0.003 (0.002)	0.003 (0.003)	0.000 (0.002)

Notes: Robust standard errors in parentheses. *** p-value<0.01, ** p-value<0.05, * p-value<0.1. Standard errors are clustered at village level. SDDS – school-aged children’s dietary diversity score; I-FVS – individual food variety score; H-DDS – household dietary diversity score; H-FCS – household food consumption score; H-FVS – household food variety score; H-MMAR – household mean micronutrient adequacy ratio.

Table 10. Relationship between dietary diversity and HAZ scores among school-aged children (6 – 14 years)

VARIABLES	Panel A – Model 1								Panel B – Model 2							
	OLS	Quantile regression							OLS	Quantile regression						
		5 th	10 th	25 th	50 th	75 th	90 th	95 th		5 th	10 th	25 th	50 th	75 th	90 th	95 th
SDDS	-0.053 (0.066)	0.035 (0.173)	0.000 (0.130)	-0.038 (0.131)	-0.040 (0.086)	-0.120** (0.059)	-0.002 (0.054)	-0.027 (0.039)	-0.405* (0.205)	-0.617 (1.210)	-0.521 (0.419)	-0.481* (0.292)	-0.431* (0.240)	-0.499*** (0.112)	-0.333 (0.228)	-0.427*** (0.155)
SDDS * Distance to closest town									0.031** (0.016)	0.050 (0.081)	0.043 (0.030)	0.040** (0.020)	0.034 (0.021)	0.035*** (0.010)	0.025 (0.017)	0.029*** (0.011)
I-FVS	0.000 (0.008)	0.012 (0.020)	0.006 (0.016)	-0.003 (0.012)	-0.005 (0.009)	-0.006 (0.008)	0.003 (0.008)	0.007 (0.008)	-0.022 (0.022)	0.059 (0.067)	0.014 (0.070)	-0.028 (0.041)	-0.041** (0.019)	-0.044* (0.024)	-0.037 (0.029)	-0.017 (0.044)
I-FVS * Distance to closest town									0.002 (0.002)	-0.004 (0.006)	-0.001 (0.006)	0.002 (0.003)	0.003** (0.001)	0.003* (0.002)	0.003 (0.002)	0.002 (0.003)
H-DDS	0.067 (0.095)	0.148 (0.240)	0.039 (0.234)	0.115 (0.114)	0.050 (0.101)	0.039 (0.102)	0.029 (0.128)	0.028 (0.070)	0.114 (0.329)	0.225 (1.120)	-0.018 (0.829)	0.356 (0.553)	-0.056 (0.349)	-0.183 (0.383)	0.038 (0.473)	0.190 (0.420)
H-DDS * Distance to closest town									-0.004 (0.027)	-0.008 (0.092)	0.009 (0.071)	-0.019 (0.043)	0.010 (0.030)	0.018 (0.029)	-0.001 (0.035)	-0.010 (0.030)
H-FCS	-0.004 (0.007)	-0.004 (0.017)	-0.008 (0.012)	-0.002 (0.008)	-0.002 (0.009)	-0.002 (0.009)	-0.003 (0.014)	0.001 (0.006)	-0.025 (0.019)	-0.056 (0.072)	-0.010 (0.050)	-0.034** (0.017)	-0.037 (0.028)	-0.050* (0.029)	-0.009 (0.026)	0.015 (0.021)
H-FCS * Distance to closest town									0.002 (0.002)	0.005 (0.006)	0.000 (0.004)	0.003* (0.002)	0.003 (0.003)	0.004* (0.002)	0.001 (0.003)	-0.001 (0.002)
H-FVS	-0.006 (0.008)	-0.003 (0.020)	-0.005 (0.014)	-0.001 (0.011)	-0.004 (0.008)	-0.002 (0.009)	-0.000 (0.010)	0.008 (0.007)	-0.016 (0.020)	0.025 (0.054)	0.018 (0.061)	-0.027 (0.040)	-0.042* (0.025)	-0.015 (0.024)	-0.015 (0.039)	0.013 (0.021)
H-FVS * Distance to closest town									0.001 (0.002)	-0.003 (0.004)	-0.002 (0.005)	0.002 (0.003)	0.003* (0.002)	0.001 (0.002)	0.001 (0.003)	-0.001 (0.002)
H-MMAR	0.001 (0.006)	-0.001 (0.014)	0.001 (0.011)	0.001 (0.010)	-0.002 (0.006)	0.007 (0.006)	0.014*** (0.005)	0.012** (0.005)	-0.003 (0.023)	0.028 (0.044)	0.007 (0.077)	-0.004 (0.033)	-0.010 (0.019)	0.017 (0.034)	0.019 (0.018)	0.014 (0.022)
H-MMAR * Distance to closest town									0.000 (0.002)	-0.003 (0.004)	-0.001 (0.006)	0.001 (0.003)	0.001 (0.002)	-0.001 (0.002)	-0.000 (0.001)	-0.000 (0.002)

Notes: Robust standard errors in parentheses. *** p-value<0.01, ** p-value<0.05, * p-value<0.1. Standard errors are clustered at village level. SDDS – school-aged children’s dietary diversity score; I-FVS – individual food variety score; H-DDS – household dietary diversity score; H-FCS – household food consumption score; H-FVS – household food variety score; H-MMAR – household mean micronutrient adequacy ratio.

Table 11. Relationship between dietary diversity and BMI among women (15 years and above)

VARIABLES	Panel A – Model 1								Panel B – Model 2							
	OLS	Quantile regression							OLS	Quantile regression						
		5 th	10 th	25 th	50 th	75 th	90 th	95 th		5 th	10 th	25 th	50 th	75 th	90 th	95 th
WDDS	-0.128 (0.152)	0.340 (0.237)	0.185 (0.275)	-0.151 (0.178)	-0.318** (0.138)	-0.182 (0.229)	-0.060 (0.318)	-0.212 (0.343)	-0.239 (0.454)	-1.374** (0.556)	-0.804 (0.576)	-0.245 (0.487)	-0.769* (0.445)	-0.418 (0.939)	0.454 (0.910)	0.629 (1.333)
WDDS * Distance to closest town									0.010 (0.036)	0.149*** (0.049)	0.092* (0.050)	0.007 (0.048)	0.040 (0.038)	0.017 (0.070)	-0.045 (0.094)	-0.075 (0.134)
I-FVS	-0.013 (0.011)	0.022 (0.019)	0.005 (0.020)	-0.013 (0.015)	-0.031** (0.013)	-0.012 (0.014)	-0.041 (0.028)	-0.015 (0.034)	-0.006 (0.036)	0.002 (0.079)	0.029 (0.057)	-0.014 (0.040)	-0.060 (0.045)	-0.012 (0.059)	0.020 (0.102)	0.151 (0.174)
I-FVS * Distance to closest town									-0.001 (0.003)	0.002 (0.006)	-0.002 (0.005)	0.000 (0.004)	0.003 (0.004)	-0.000 (0.004)	-0.005 (0.008)	-0.013 (0.012)
H-DDS	-0.022 (0.127)	0.100 (0.117)	0.181 (0.158)	0.006 (0.198)	-0.029 (0.165)	-0.143 (0.152)	-0.315 (0.352)	-0.430* (0.220)	0.362 (0.476)	0.272 (1.163)	0.592 (0.835)	0.491 (0.476)	0.195 (0.750)	0.074 (0.525)	0.524 (1.373)	1.821 (1.164)
H-DDS * Distance to closest town									-0.032 (0.036)	-0.016 (0.097)	-0.034 (0.069)	-0.043 (0.034)	-0.016 (0.053)	-0.016 (0.041)	-0.067 (0.112)	-0.173** (0.084)
H-FCS	0.001 (0.010)	0.006 (0.023)	-0.004 (0.013)	-0.008 (0.014)	0.003 (0.013)	-0.003 (0.013)	-0.006 (0.021)	-0.003 (0.018)	-0.002 (0.036)	0.038 (0.096)	0.006 (0.052)	-0.009 (0.041)	0.000 (0.043)	-0.017 (0.046)	0.020 (0.057)	0.121 (0.076)
H-FCS * Distance to closest town									0.000 (0.003)	-0.003 (0.010)	-0.001 (0.004)	0.000 (0.003)	0.000 (0.004)	0.001 (0.003)	-0.002 (0.005)	-0.010** (0.005)
H-FVS	0.003 (0.010)	0.029** (0.014)	0.017 (0.012)	0.008 (0.012)	0.007 (0.014)	0.003 (0.014)	-0.023 (0.018)	-0.027 (0.024)	0.000 (0.031)	0.009 (0.039)	-0.014 (0.044)	-0.016 (0.030)	0.008 (0.046)	0.029 (0.048)	0.054 (0.054)	0.087 (0.126)
H-FVS * Distance to closest town									0.000 (0.003)	0.002 (0.004)	0.003 (0.004)	0.002 (0.003)	-0.000 (0.004)	-0.002 (0.004)	-0.006 (0.004)	-0.009 (0.009)
H-MMAR	0.002 (0.009)	0.029** (0.011)	0.011 (0.012)	0.005 (0.009)	0.007 (0.015)	-0.002 (0.014)	-0.018 (0.025)	-0.011 (0.016)	0.022 (0.032)	-0.018 (0.038)	0.024 (0.048)	0.000 (0.036)	0.047 (0.045)	0.042 (0.037)	0.030 (0.052)	0.036 (0.074)
H-MMAR * Distance to closest town									-0.002 (0.002)	0.004 (0.003)	-0.001 (0.004)	0.000 (0.003)	-0.003 (0.003)	-0.003 (0.003)	-0.004 (0.004)	-0.004 (0.006)

Notes: Robust standard errors in parentheses. *** p-value<0.01, ** p-value<0.05, * p-value<0.1. Standard errors are clustered at village level. WDDS – women’s dietary diversity score; I-FVS – individual food variety score; H-DDS – household dietary diversity score; H-FCS – household food consumption score; H-FVS – household food variety score; H-MMAR – household mean micronutrient adequacy ratio.

6. Discussion and conclusions

We study the association between DD and anthropometric outcomes of children and women in the RUI of Bangalore. Together with OLS regression, we apply the QR method to cast light on the heterogeneity of this relationship along the distribution of anthropometric outcomes. 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 demographic groups – young children, school-aged children, and women.

We find that none of the associations between DD and anthropometric outcomes for young children, school-aged children, and women are significant at the mean. However, QR results suggest that there are some heterogeneities in the relationship, although they are not consistent across different DD measures. The most consistent heterogeneity is observed for lower quantiles of the WAZ distribution for young children. Increasing DD for young children is associated with higher WAZ at lower quantiles, which means a lower prevalence of undernutrition. This is consistent with findings from many other Indian studies. For some measures of DD, the coefficient is positive and significant for both young children (WHZ score) and school-aged children (BMI z-score) at upper quantiles. Similar to Young et al. (2020), this indicates that increasing DD is associated with a higher prevalence of overweight/obesity. We also observe a negative association between DD and height-based outcomes for both young and school-aged children. This is an adverse association and is contrary to what is expected. Similar results are also found in a study by Amugsi et al. (2017) for children aged 6 to 23 months in Nigeria. Further research is needed to disentangle the complexities involved in this adverse relationship between DD and HAZ at the upper quantiles. 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.

While many studies on the relationship between DD and health outcomes use location (rural/urban) as a control variable, very few examine whether the relationship varies between the two locations (Arimond and Ruel 2002). As mentioned above, the evidence so far is mixed. Furthermore, analysis based on a

binary distinction between rural and urban is only able to capture the mechanisms operating within these respective regions and does not allow for interaction between the two. In the complex and dynamic RUI setting, however, the nature of the relationship between DD and anthropometric outcomes might vary. We therefore include an interaction variable between DD and distance to the closest town in our model. This also leads to mixed results. While increasing DD improves WAZ score for children in middle quantiles of WAZ distribution in areas closer to town, this does not hold for children at upper quantiles. Similarly, at upper quantiles for both young children (WHZ score) and women, increasing DD is associated with increased prevalence of overweight/obesity among those living closer to a town. Thus, policies focusing on improving DD in this specific setting will not always be effective in improving anthropometric outcomes, and may even be counter-productive for different sub-sections of the population.

Overall, our finding that the relationship between DD and nutritional outcomes varies across the distributions of these outcomes is not unexpected. While consumption of a higher number of food items or food groups may indicate higher micronutrient intake, this can often be accompanied by excess energy intake. Urbanization, globalization, economic growth, and the spread of supermarkets have led to improvements in access and the affordability of diversified as well as energy-dense diets for households in many LMICs, including India (Pingali, 2007; Popkin, 2009). In such contexts, increasing DD might lead to excess energy intake. In our sample, animal-sourced food and fish are the least consumed food groups. Increasing DD would imply increasing consumption of these food groups. However, if this increased DD is due to consumption of processed meat (availability of which increases as one lives closer to a town), it may increase weight as well.

As mentioned before, the ambiguous evidence in the literature could be due to varied definitions of DD. This is illustrated in our results as well. The sign and significance of coefficients capturing the relationship between DD and anthropometric outcomes vary for different measures of DD. Thus, depending on which indicator is used in a study, it might arrive at different conclusions. The variability in results is quite large, and it is not possible for us to conclude that a particular measure of DD is better than others; each has its strengths and weaknesses. Using several complementary DD measures might

provide more robust results and improve our understanding of the relationship between DD and anthropometric outcomes.

Another point to note is that 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. The current most commonly used measures are more suitable for areas with limited access to processed food.

Several limitations of our study should be noted. First, 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. Second, father's height is an important factor associated with the anthropometric outcomes of children. Due to the unavailability of this data, we have not included it in our model. Several studies such as Kim et al. (2019) and Li et al. (2020) include paternal characteristics as a secondary analysis for countries where data are available. Their estimated relationship between DD and anthropometric outcomes is not affected by the inclusion of paternal controls. Third, there might be a recall bias in DD for young and school-aged children as mothers might not remember all foods consumed or be fully informed about the food that their children have consumed away from home. While the enumerators were trained to probe well, we cannot rule out recall bias completely.

6.1 Policy Implications

The results of our study reveal that for some individuals (young children with high WHZ scores and school-aged children with high BMI z-scores) increasing DD is associated with unhealthy outcomes. Rapid urbanization has led to the growth of cities and created RUI environments in many LMICs that are 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 policy needs to be more nuanced to ensure that higher DD is not accompanied by higher consumption of unhealthy foods. For instance, while the Indian

government's ***Poshan Abhiyan*** initiative focuses on increasing the consumption of iron-rich foods to reduce anemia, it should also focus on educating people about reducing the consumption of unhealthy foods, especially in areas with higher access to processed food.

The global nutrition monitoring framework includes DD as one of the indicators to measure the 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 currently used, 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 multiple factors and complex interactions among them. According to some studies for India (Corsi et al., 2016; Kim et al., 2019; 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 nutrition policy that accounts for multiple inputs rather than focusing on any single aspect.

References

- Abris, G.P., Provido, S.M.P., Hong, S., Yu, S.H., Lee, C.B., Lee, J.E., 2018. Association between dietary diversity and obesity in the Filipino Women's Diet and Health Study (FiLWHEL): A cross-sectional study. *PLOS ONE* 13, e0206490. <https://doi.org/10.1371/journal.pone.0206490>.
- Agrawal, S., Kim, R., Gausman, J., Sharma, S., Sankar, R., Joe, W., Subramanian, S.V., 2019. Socio-economic patterning of food consumption and dietary diversity among Indian children: evidence from NFHS-4. *Eur J Clin Nutr* 73, 1361–1372. <https://doi.org/10.1038/s41430-019-0406-0>.
- Aiyar, A., Rahman, A., Pingali, P., 2021. India's rural transformation and rising obesity burden. *World Development* 138, 105258. <https://doi.org/10.1016/j.worlddev.2020.105258>.
- Amugsi, D., Mittelmark, M.B., Iartey, A., 2014. Dietary Diversity is a Predictor of Acute Malnutrition in Rural but Not in Urban Settings: Evidence from Ghana. *BJMMR* 4, 4310–4324. <https://doi.org/10.9734/bjmmr/2014/10014>.
- Amugsi, D.A., Dimbuene, Z.T., Bakibinga, P., Kimani-Murage, E.W., Haregu, T.N., Mberu, B., 2016. Dietary diversity, socioeconomic status and maternal body mass index (BMI): quantile regression analysis of nationally representative data from Ghana, Namibia and Sao Tome and Principe. *BMJ Open* 6, e012615. <https://doi.org/10.1136/bmjopen-2016-012615>.
- Amugsi, D.A., Dimbuene, Z.T., Kimani-Murage, E.W., Mberu, B., Ezeh, A.C., 2017. Differential effects of dietary diversity and maternal characteristics on linear growth of children aged 6-59 months in sub-Saharan Africa: a multi-country analysis. *Public Health Nutrition* 20, 1029–1045. <https://doi.org/10.1017/s1368980016003426>.
- Arimond, M., Ruel, M.T., 2002. Progress in developing an infant and a child feeding index: an example using the Ethiopia Demographic and Health Survey 2000. FCND Discussion paper 143. International Food Policy Research Institute, Washington, D. C. (accessed 16 December 2020).
- Asghari, G., Mirmiran, P., Yuzbashian, E., Azizi, F., 2017. A systematic review of diet quality indices in relation to obesity. *British Journal of Nutrition* 117, 1055–1065. <https://doi.org/10.1017/S0007114517000915>.
- Azadbakht, L., Esmailzadeh, A., 2011. Dietary diversity score is related to obesity and abdominal adiposity among Iranian female youth. *Public Health Nutrition* 14, 62–69. <https://doi.org/10.1017/S1368980010000522>.
- Bharadwaj, K.A., 2017. Bengaluru's population to shoot up to 20.3 million by 2031. *The Hindu*.
- Borkotoky, K., Unisa, S., Gupta, A.K., 2018. State-level dietary diversity as a contextual determinant of nutritional status of children in India: A multilevel approach. *Journal of Biosocial Science* 50, 26–52. <https://doi.org/10.1017/S0021932017000013>.
- Bren d'Amour, C., Pandey, B., Reba, M., Ahmad, S., Creutzig, F., Seto, K.C., 2020. Urbanization, processed foods, and eating out in India. *Global Food Security* 25, 100361. <https://doi.org/10.1016/j.gfs.2020.100361>.

- Cawley, J., 2015. An economy of scales: A selective review of obesity's economic causes, consequences, and solutions. *Journal of health economics* 43, 244–268. <https://doi.org/10.1016/j.jhealeco.2015.03.001>.
- Chagomoka, T., Drescher, A., Glaser, R., Marschner, B., Schlesinger, J., Nyandoro, G., 2016. Women's dietary diversity scores and childhood anthropometric measurements as indices of nutrition insecurity along the urban-rural continuum in Ouagadougou, Burkina Faso. *Food & Nutrition Research* 60, 29425. <https://doi.org/10.3402/fnr.v60.29425>.
- Chandrasekhar, S., Aguayo, V.M., Krishna, V., Nair, R., 2017. Household food insecurity and children's dietary diversity and nutrition in India. Evidence from the comprehensive nutrition survey in Maharashtra. *Maternal & Child Nutrition* 13 Suppl 2. <https://doi.org/10.1111/mcn.12447>.
- Cohen, B., 2006. Urbanization in developing countries: Current trends, future projections, and key challenges for sustainability. *Technology in Society* 28, 63–80. <https://doi.org/10.1016/j.techsoc.2005.10.005>.
- Corsi, D.J., Mejía-Guevara, I., Subramanian, S.V., 2016. Risk factors for chronic undernutrition among children in India: Estimating relative importance, population attributable risk and fractions. *Social science & medicine* (1982) 157, 165–185. <https://doi.org/10.1016/j.socscimed.2015.11.014>.
- Darapheak, C., Takano, T., Kizuki, M., Nakamura, K., Seino, K., 2013. Consumption of animal source foods and dietary diversity reduce stunting in children in Cambodia. *Int Arch Med* 6, 29. <https://doi.org/10.1186/1755-7682-6-29>.
- Denis, E., Mukhopadhyay, P., Zérah, M.-H., 2012. Subaltern Urbanization in India. *Economic and Political Weekly* 47, 52–62.
- Directorate of Census Operations Karnataka, 2011. Census of India 2011: Karnataka, district census handbook, Bangalore: (Series-30 No. Part XII-A), 476 pp.
- Ellis, P., Roberts, M., 2015. Leveraging Urbanization in South Asia: Managing Spatial Transformation for Prosperity and Livability. Washington, D. C.
- Frempong, R.B., Annim, S.K., 2017. Dietary diversity and child malnutrition in Ghana. *Heliyon* 3, e00298. <https://doi.org/10.1016/j.heliyon.2017.e00298>.
- Gausman, J., Perkins, J.M., Lee, H.-Y., Mejia-Guevara, I., Nam, Y.-S., Lee, J.-K., Oh, J., Subramanian, S.V., 2018. Ecological and social patterns of child dietary diversity in India: a population-based study. *Nutrition* (Burbank, Los Angeles County, Calif.) 53, 77–84. <https://doi.org/10.1016/j.nut.2018.01.006>.
- Gupta, S., Sunder, N., Pingali, P.L., 2020. Are Women in Rural India Really Consuming a Less Diverse Diet? *Food Nutr Bull* 41, 318–331. <https://doi.org/10.1177/0379572120943780>.
- Hatløy, A., Hallund, J., Diarra, M.M., Oshaug, A., 2000. Food variety, socioeconomic status and nutritional status in urban and rural areas in Koutiala (Mali). *Public Health Nutr.* 3, 57–65. <https://doi.org/10.1017/s1368980000000628>.

- Hawkes, C., Harris, J., Gillespie, S., 2017. Changing diets: Urbanization and the Nutrition Transition. International Food Policy Research Institute, Washington, DC.
- Heemann, M., Kim, R., Vollmer, S., Subramanian, S.V., 2021. Assessment of Undernutrition Among Children in 55 Low- and Middle-Income Countries Using Dietary and Anthropometric Measures. *JAMA Netw Open* 4, e2120627. <https://doi.org/10.1001/jamanetworkopen.2021.20627>.
- Henjum, S., Torheim, L.E., Thorne-Lyman, A.L., Chandyo, R., Fawzi, W.W., Shrestha, P.S., Strand, T.A., 2015. Low dietary diversity and micronutrient adequacy among lactating women in a peri-urban area of Nepal. *Public Health Nutrition* 18, 3201–3210. <https://doi.org/10.1017/S1368980015000671>.
- Hoddinott, J., Maluccio, J.A., Behrman, J.R., Flores, R., Martorell, R., 2008. Effect of a nutrition intervention during early childhood on economic productivity in Guatemalan adults. *The Lancet* 371, 411–416. [https://doi.org/10.1016/S0140-6736\(08\)60205-6](https://doi.org/10.1016/S0140-6736(08)60205-6).
- Hoffmann, E., Jose, M., Nölke, N., Möckel, T., 2017. Construction and Use of a Simple Index of Urbanisation in the Rural–Urban Interface of Bangalore, India. *Sustainability* 9, 2146. <https://doi.org/10.3390/su9112146>.
- INDEX Project, 2018a. Data4Diets: Building Blocks for Diet-related Food Security Analysis. Mean Adequacy Ratio (MAR). Tufts University. <https://index.nutrition.tufts.edu/data4diets/indicator/mean-adequacy-ratio-mar> (accessed 31 August 2021).
- INDEX Project, 2018b. Data4Diets: Building Blocks for Diet-related Food Security Analysis. Tufts University, Boston, MA, 4 pp. <https://index.nutrition.tufts.edu/data4diets> (accessed 7 January 2020).
- Kennedy, G., Ballard, T., Dop, M., 2011. Guidelines for measuring household and individual dietary diversity ISBN 978-92-5-106749-9. Food and Agriculture Organization of the United Nations, Rome, Italy (accessed 12.16.2020).
- Kheirouri, S., Alizadeh, M., 2021. Maternal dietary diversity during pregnancy and risk of low birth weight in newborns: a systematic review. *Public Health Nutrition* 24, 4671–4681. <https://doi.org/10.1017/S1368980021000276>.
- Kim, R., Mejía-Guevara, I., Corsi, D.J., Aguayo, V.M., Subramanian, S.V., 2017. Relative importance of 13 correlates of child stunting in South Asia: Insights from nationally representative data from Afghanistan, Bangladesh, India, Nepal, and Pakistan. *Social science & medicine* (1982) 187, 144–154. <https://doi.org/10.1016/j.socscimed.2017.06.017>.
- Kim, R., Rajpal, S., Joe, W., Corsi, D.J., Sankar, R., Kumar, A., Subramanian, S.V., 2019. Assessing associational strength of 23 correlates of child anthropometric failure: An econometric analysis of the 2015-2016 National Family Health Survey, India. *Social science & medicine* (1982) 238, 112374. <https://doi.org/10.1016/j.socscimed.2019.112374>.

- Li, Z., Kim, R., Vollmer, S., Subramanian, S.V., 2020. Factors Associated With Child Stunting, Wasting, and Underweight in 35 Low- and Middle-Income Countries. *JAMA Netw Open* 3, e203386. <https://doi.org/10.1001/jamanetworkopen.2020.3386>.
- Marshall, S., Burrows, T., Collins, C.E., 2014. Systematic review of diet quality indices and their associations with health-related outcomes in children and adolescents. *Journal of Human Nutrition and Dietetics* 27, 577–598. <https://doi.org/10.1111/jhn.12208>.
- McDonald, C.M., McLean, J., Kroeun, H., Talukder, A., Lynd, L.D., Green, T.J., 2015. Household food insecurity and dietary diversity as correlates of maternal and child undernutrition in rural Cambodia. *Eur J Clin Nutr* 69, 242–246. <https://doi.org/10.1038/ejcn.2014.161>.
- Menon, P., Bamezai, A., Subandoro, A., Ayoya, M.A., Aguayo, V.M., 2015. Age-appropriate infant and young child feeding practices are associated with child nutrition in India: insights from nationally representative data. *Maternal & Child Nutrition* 11, 73–87. <https://doi.org/10.1111/mcn.12036>.
- Meshram, I.I., Mallikharjun Rao, K., Balakrishna, N., Harikumar, R., Arlappa, N., Sreeramakrishna, K., Laxmaiah, A., 2019. Infant and young child feeding practices, sociodemographic factors and their association with nutritional status of children aged <3 years in India: findings of the National Nutrition Monitoring Bureau survey, 2011-2012. *Public Health Nutrition* 22, 104–114. <https://doi.org/10.1017/S136898001800294X>.
- Miller, V., Webb, P., Micha, R., Mozaffarian, D., 2020. Defining diet quality: a synthesis of dietary quality metrics and their validity for the double burden of malnutrition. *The Lancet Planetary Health* 4, e352-e370. [https://doi.org/10.1016/s2542-5196\(20\)30162-5](https://doi.org/10.1016/s2542-5196(20)30162-5).
- Mittal, N., Vollmer, S., 2020. The Double Burden of Malnutrition in Bangalore, India. *Hidden Hunger and the Transformation of Food Systems* 121, 138–148. <https://doi.org/10.1159/000507521>.
- National Portal of India, 2018. POSHAN ABHIYAAN - PM's Overarching Scheme for Holistic Nourishment. <https://www.india.gov.in/spotlight/poshan-abhiyaan-pms-overarching-scheme-holistic-nourishment> (accessed 1 February 2021).
- NFHS-4, 2015-16. National Family Health Survey: India Fact Sheet. Ministry of Health and Family Welfare, Mumbai, 8 pp. (accessed 12.16.2020).
- NFHS-5, 2019-20. National Family Health Survey (NFHS-5): District Fact Sheet - Bangalore, Karnataka. Ministry of Health and Family Welfare, Government of India. http://rchiips.org/nfhs/districtfactsheet_NFHS-5.shtml (accessed 31 August 2021).
- Nithya, D.J., Bhavani, R.V., 2016. Do Dietary Diversity Indices Reflect the Nutritional Status of School Aged Children? *IJND* 53, 405. <https://doi.org/10.21048/ijnd.2016.53.4.8399>.
- Nithya, D.J., Bhavani, R.V., 2018. Dietary diversity and its relationship with nutritional status among adolescents and adults in rural India. *Journal of Biosocial Science* 50, 397–413. <https://doi.org/10.1017/s0021932017000463>.
- Oliveira Otto, M.C. de, Anderson, C.A.M., Dearborn, J.L., Ferranti, E.P., Mozaffarian, D., Rao, G., Wylie-Rosett, J., Lichtenstein, A.H., 2018. Dietary Diversity: Implications for Obesity Prevention

- in Adult Populations: A Science Advisory From the American Heart Association. *Circulation* 138, e160-e168. <https://doi.org/10.1161/CIR.0000000000000595>.
- Patton, G.C., Sawyer, S.M., Santelli, J.S., Ross, D.A., Afifi, R., Allen, N.B., Arora, M., Azzopardi, P., Baldwin, W., Bonell, C., Kakuma, R., Kennedy, E., Mahon, J., McGovern, T., Mokdad, A.H., Patel, V., Petroni, S., Reavley, N., Taiwo, K., Waldfogel, J., Wickremarathne, D., Barroso, C., Bhutta, Z., Fatusi, A.O., Mattoo, A., Diers, J., Fang, J., Ferguson, J., Ssewamala, F., Viner, R.M., 2016. Our future: a Lancet commission on adolescent health and wellbeing. *The Lancet* 387, 2423–2478. [https://doi.org/10.1016/S0140-6736\(16\)00579-1](https://doi.org/10.1016/S0140-6736(16)00579-1).
- Perkins, J.M., Jayatissa, R., Subramanian, S.V., 2018. Dietary diversity and anthropometric status and failure among infants and young children in Sri Lanka. *Nutrition* (Burbank, Los Angeles County, Calif.) 55-56, 76–83. <https://doi.org/10.1016/j.nut.2018.03.049>.
- Pingali, P., 2007. Westernization of Asian diets and the transformation of food systems: Implications for research and policy. *Food Policy* 32, 281–298. <https://doi.org/10.1016/j.foodpol.2006.08.001>.
- Pingali, P., Mittra, B., Rahman, A., 2017. The bumpy road from food to nutrition security – Slow evolution of India's food policy. *Global Food Security* 15, 77–84. <https://doi.org/10.1016/j.gfs.2017.05.002>.
- Popkin, B.M., 1993. Nutritional Patterns and Transitions. *Population and Development Review* 19, 138–157. <https://doi.org/10.2307/2938388>.
- Popkin, B.M., 2009. Global changes in diet and activity patterns as drivers of the nutrition transition. Nestle Nutrition workshop series. *Paediatric programme* 63, 1-10; discussion 10-4, 259-68. <https://doi.org/10.1159/000209967>.
- Prentice, A.M., Ward, K.A., Goldberg, G.R., Jarjou, L.M., Moore, S.E., Fulford, A.J., Prentice, A., 2013. Critical windows for nutritional interventions against stunting. *Am J Clin Nutr* 97, 911–918. <https://doi.org/10.3945/ajcn.112.052332>.
- Rah, J.H., Akhter, N., Semba, R.D., Pee, S. de, Bloem, M.W., Campbell, A.A., Moench-Pfanner, R., Sun, K., Badham, J., Kraemer, K., 2010. Low dietary diversity is a predictor of child stunting in rural Bangladesh. *Eur J Clin Nutr* 64, 1393–1398. <https://doi.org/10.1038/ejcn.2010.171>.
- Saaka, M., Osman, S.M., 2013. Does Household Food Insecurity Affect the Nutritional Status of Preschool Children Aged 6–36 Months? *International Journal of Population Research* 2013, 1–12. <https://doi.org/10.1155/2013/304169>.
- Salehi-Abargouei, A., Akbari, F., Bellissimo, N., Azadbakht, L., 2016. Dietary diversity score and obesity: a systematic review and meta-analysis of observational studies. *Eur J Clin Nutr* 70, 1–9. <https://doi.org/10.1038/ejcn.2015.118>.
- Savy, M., Martin-Prével, Y., Danel, P., Traissac, P., Dabiré, H., Delpeuch, F., 2008. Are dietary diversity scores related to the socio-economic and anthropometric status of women living in an urban area in Burkina Faso? *Public Health Nutr*. 11, 132–141. <https://doi.org/10.1017/s1368980007000043>.

- Steinhübel, L., Cramon-Taubadel, S. von, 2020. Somewhere in between Towns, Markets and Jobs – Agricultural Intensification in the Rural–Urban Interface. *Journal of Development Studies*, 1–26. <https://doi.org/10.1080/00220388.2020.1806244>.
- Sudhira, H.S., Ramachandra, T.V., Subrahmanya, M.B., 2007. Bangalore. *Cities* 24, 379–390. <https://doi.org/10.1016/j.cities.2007.04.003>.
- Swindale, A., Bilinsky, P., 2006. Household Dietary Diversity Score (HDDS) for Measurement of Household Food Access: Indicator Guide (Version 2) FHI 360/FANTA. USAID, Washington, D. C., 15 pp. (accessed 12.16.2020).
- UNICEF, 2018. Improving breastfeeding, complementary foods and feeding practices. https://sites.unicef.org/nutrition/index_breastfeeding.html (accessed 1 February 2021).
- Varkey, A.M., 2018. Ever-growing Bengaluru and ineffective planning. DH News Service.
- Victora, C.G., Adair, L., Fall, C., Hallal, P.C., Martorell, R., Richter, L., Sachdev, H.S., 2008. Maternal and child undernutrition: consequences for adult health and human capital. *The Lancet* 371, 340–357. [https://doi.org/10.1016/S0140-6736\(07\)61692-4](https://doi.org/10.1016/S0140-6736(07)61692-4).
- WHO, 2017. Global nutrition monitoring framework: Operational guidance for tracking progress in meeting targets for 2025. <https://www.who.int/publications/i/item/9789241513609> (accessed 1 February 2021).
- WHO, 2020. Healthy diet. <https://www.who.int/news-room/fact-sheets/detail/healthy-diet> (accessed 1 February 2021).
- Young, M.F., Nguyen, P., Tran, L.M., Avula, R., Menon, P., 2020. A Double Edged Sword? Improvements in Economic Conditions over a Decade in India Led to Declines in Undernutrition as Well as Increases in Overweight among Adolescents and Women. *J Nutr* 150, 364–372. <https://doi.org/10.1093/jn/nxz251>.