Hunger and Health: Reexamining the Impact of Household Food Insecurity on Child Malnutrition in India*

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Abstract

Child malnutrition is remarkably high in India. The problem of food insecurity is also extremely alarming in the country. From a policy perspective, a question of paramount importance in this context is: are these two problems inter-related? Answering this question based on existing literature is difficult. This is because literature examining specifically the effect of food insecurity on child/adolescent malnutrition in India is scarce. Besides, the small number of studies that do examine this question empirically find mixed evidence. In light of this, here we reexamine the effect of food insecurity on child malnutrition using data from the Young Lives survey. Employing several contemporary econometric approaches, we not only estimate the mean effect but also the distributional effects of food insecurity on child malnutrition. We find evidence of sizeable negative average effects of food insecurity on children's anthropometric indices for nutrition surveillance including weight-for-age z score (WAZ) and height-for-age z-score (HAZ). Further, we document important heterogeneity in the effect of food insecurity on children's WAZ and HAZ across the outcome-distributions. Our results suggest that expansion of policies that could effectively reduce household food insecurity is vital to address the problem of malnutrition among Indian children.

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Keywords: Child malnutrition, Food insecurity, Health, India.

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1 Introduction

Child malnutrition is one of the most pressing public health issues currently in India. According to the Global Hunger Index report (FAO, 2019), India recorded the highest child wasting rate of any country at 20.8% in 2019. Moreover, roughly 38% of children under the age of five are affected by stunting in India (FAO, 2019; Von Grebmer et al., 2019; Swaminathan et al., 2019). The Sustainable Development Framework (2018) reports that nearly 4 out of 10 children in India do not meet their full human potential owing to chronic malnutrition. Besides, with 1 in every 3 children malnourished, malnutrition is also thought to be the predominant risk factor for deaths in children under five, accounting for 68.2% of the total under-five deaths (Kaur, 2019).

Equally alarming is India's food security crisis. Food security is described as 'a situation that exists when all people, at all times, have physical, social, and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life' (FAO, 2019). The State of Food Security and Nutrition in the World (SOFI) report (FAO, IFAD, UNICEF, WFP and WHO, 2020) shows that while 27.8% of India's population suffered from moderate or severe food insecurity in 2014-16, the proportion rose to 31.6% in 2017-19. The number of food insecure people grew from 426.5 million in 2014-16 to 488.6 million in 2017-19. India accounted for 22% of the global burden of food insecurity, the highest for any country, in 2017-19. Currently, India ranks 94th among 107 countries according to the Global Hunger Index 2020 (Von Grebmer et al., 2019).

From a policy perspective, a question of paramount importance in this context is: are these two problems inter-related? More specifically, can the food security crisis in India be held responsible for the child and adolescent malnutrition problem? Unfortunately, answering this question unambiguously based on the existing literature is extremely difficult. This is because the literature specifically examining the effect of food insecurity on child and adolescent malnutrition in India, quite surprisingly, is scarce.[1] And the small number of studies that do examine this question empirically, even their findings are mixed and somewhat confusing. For instance, using data for children from Andhra Pradesh, Humphries et al. (2015) find evidence of a negative association between food insecurity and anthropometric nutritional status indices, although the association attenuates after controlling for other covariates. Chandrasekhar et al. (2017) using data from Maharashtra, find that children from food insecure households have a higher likelihood of stunting, wasting and low-birthweight, although food security status of households loses importance once diet diversity is taken into account. Similar findings are reported by Pathak et al. (2020) using data from a district in North East India. In complete contrast to these studies, however, Joe et al. (2019) using data from National Nutrition Monitoring Bureau Urban Nutrition Study 2013–2015 find weak-to-null correlation between anthropometric failures and food insecurity. Based on their findings, they conclude dietary intake alone may have limited impact on curbing the complex phenomenon of anthropometric failure. In line with Joe et al. (2019), Aguayo et al. (2016), also find no effect of food insecurity on children's anthropometric measures or likelihood of stunting using data from Comprehensive Nutrition Survey in Maharashtra (CNSM).[2]

In light of this, our paper makes a fresh and careful attempt to examine the relationship between food insecurity and child malnutrition in context of India. Specifically, we estimate (i) the *average* effect of food insecurity on child malnutrition employing various contemporary econometric approaches, including propensity score matching, inverse propensity weighting estimator, and comparisons of the selection on unobservable and observable estimators, and (ii) the *distributional* effects of food insecurity on child malnutrition by employing conditional and unconditional quantile treatment effect (QTE) estimators. Estimation of distributional effects, in addition to the average effect, allows us to test whether the impact of food insecurity is constant across the outcome distribution of children or whether food insecurity affects children at different parts of the outcome distribution differently. Thus our research enables us not only to provide an answer to the question, 'does food insecurity lead to child malnutrition?' but, also to the question, 'are some children affected more by food insecurity than others?'.

There are several pathways from household food insecurity to child malnutrition. First, household food insecurity can directly lead to malnutrition among children through compromised diets. Indeed, as noted by Dunifon and Kowaleski-Jones (2003), children in households where the availability of food is threatened, are more likely to have limited access to nutritious foods. Second, food insecurity can lead to a compromised immune system of children increasing their risk of infections/diseases, thereby making them more prone to malnutrition (infection-malnutrition cycle)(Fischer et al., 2014). Third, maternal ill-health, specifically anaemia and maternal depressive symptoms, owing to insufficient perinatal nutrition, can result in low birth-weight and stunting in infants (Swaminathan et al., 2019; Smedley et al., 2000; Casey et al., 2004; Corsi et al., 2016).[3] Fourth, household food insecurity can lead to stress, anxiety and depression among parents which in turn could impact infant feeding in a way that causes child stunting, wasting, and micronutrient deficiencies (WHO, 2018).

To investigate this relationship in the context of India, we utilize data from the Young Lives Survey (YLS). YLS is an international longitudinal study of childhood poverty following the lives of 12,000 children in India, Ethiopia, Peru and Vietnam over 15 years. In India, the first comprehensive wave of the survey was conducted in 2002 among children belonging to two different age cohorts, a younger cohort (children aged between 6 and 21 months) and an older cohort (children aged between 7.5 and 8.5 years), in the state of Andhra Pradesh. Successive rounds of the survey that followed the same children belonging to the two cohorts were conducted in 2006-07, 2009-10, 2013-14, and 2016-17. We measure food insecurity at the household level and consider a household as food insecure if it was moderately or severely food insecure as per the Household Food Insecurity Access Scale (HFIAS) (see Section 3 for further details). We measure child and adolescent malnutrition using two widely used anthropometric indices for nutrition surveillance: height-for-age z-score (HAZ) and weight-for-age z-score (WAZ).

Our results are compelling. The OLS with comprehensive controls suggest that WAZ (HAZ) of children who belong to food insecure households is, on average, 0.10 SD (0.07 SD) lower than the WAZ (HAZ) of children who belong to food secure households. The results obtained using propensity score matching estimation and inverse propensity weighting estimation are consistent with the OLS results, and if anything point to a stronger negative average effect of food insecurity on WAZ and HAZ. Using Oster (2019) approach that measures the sensitivity of treatment parameters when the ratio of selection on unobservables to selection on observables varies from a minimum of zero to a maximum of unity, we find that our OLS results are robust to sufficiently high degrees of selection on unobservables. Based on the estimates of conditional and unconditional QTEs, we further find that while food insecurity adversely affects health of all children, there is considerable variation in the effect across the distribution of WAZ and HAZ. In particular, our results suggest that the adverse effect of food insecurity on health of children is likely to be more severe for children belonging towards the upper end of the health distribution than those belonging towards the lower end. These results underscore the importance of expansion of government policies and programs that could effectively reduce food insecurity in addressing the problem of malnutrition among Indian children.

Our work relates to at least two strands of the literature. It relates to the literature that examines the determinants of child malnutrition specifically in India. The papers in this literature that focus on food insecurity as a potential determinant of child malnutrition have already been discussed above. Important papers that focus on other determinants of child malnutrition (e.g., household socioeconomic status, sanitation, son preference, etc.) include Spears (2012a,b, 2013, 2020); Fenske et al. (2013); Desai and Vanneman (2015); Dobe (2015); Hammer and Spears (2016); Jayachandran and Pande (2017); Singh et al. (2017); Spears (2020); Huey et al. (2019); Kanjilal et al. (2010); McKay et al. (2020) and Rehan et al. (2020). Our work also relates to the literature that analyzes the associations between food security and child malnutrition using cross-country data or data from surveys conducted in other developing countries. Among the noteworthy papers in this literature are Hackett et al. (2009) (Colombia), Saha et al. (2009) (Bangladesh), Osei et al. (2010) (Nepal), Psaki et al. (2012) (multiple countries), Saaka and Osman (2013) (Ghana), Naser et al. (2014) (Malaysia), Mutisya et al. (2015) (Kenya), Abdurahman et al. (2016) (Ethiopia), Kim et al. (2017) (multiple countries), Mulu and Mengistie (2017) (Ethiopia), Chakona and Shackleton (2018) (South Africa), Drysdale et al. (2021) (South Africa), etc.

The remainder of the paper is organized as follows. Section 2 discusses the context of this study. Section 3 outlines the data used for our analysis, followed by the empirical strategies in Section 4. We present the results in Section 5. Section 6 concludes.

2 Background

With approximately 194 million people estimated as undernourished in 2018 (FAO, 2019), survey and media reports indicate that India is slipping into a vicious cycle of malnutrition (Singh and Pandey, 2018). This, in spite of the agriculture sector recording its highest growth from 2003-04 to 2012 along with improvements in foodgrain production (GOI, 2015, 2016). The realization of growth has not trickled down to reflect improvements in nutritional calorie intake (GOI, 2014; Panagariya and More, 2014). Malnutrition, aside from being a major factor for death, also remains the leading risk factor for disease burden and health loss in children across India. To deal with the challenge of malnutrition, in early 2018, India launched its National Nutrition Mission (NNM) under the umbrella of the Integrated Child Development Services (ICDS) scheme. The overarching goal of the NNM is to achieve improvements in the nutritional status of children from 0-6 years, adolescent girls, pregnant women and lactating mothers. The mission aims to reduce stunting, undernutrition, anaemia among young children, women and adolescent girls, and reduce low birth weight amongst babies. At present, Swaminathan et al. (2019) document the prevalence of low birthweight to be 21.4%, stunting 39.3%, wasting 15.7%, underweight 32.7%, anaemia in children 59.7%, anaemia in women aged 15 - 49 years of age 54.4%, and overweight at 11.5%. They also note that these trends extrapolated for the indicators in the NNM 2022 suggest notable gaps between the projected prevalence and the government's targets. Hence, substantial improvements in the indicators of malnutrition would require effective improvements in the determinants of child health across the life cycle, one of which is food insecurity.

In terms of food insecurity, only about 9.2% of children between 6 and 23 months of age are fed a minimum acceptable diet in India (Von Grebmer et al., 2019). With the aim to expand its current food aid program to tackle persistently high levels of food insecurity, the Government of India enacted the National Food Security Act on July 5, 2013. The Act marks a paradigm shift in the approach to food security from a welfare to a rights based approach. It legally entitles up to 75% of the rural and 50% of the urban population to receive subsidized foodgrains under the Targeted Public Distribution System (TPDS). Beneficiaries that constitute the poorest of the poor are entitled to 35 kg of foodgrains per family per month, and the priority households are entitled to 5 kg of food grains per person per month. The Act also proposes daily free meal entitlement and nutritional support to specific groups like pregnant women and lactating mothers; and children between the ages of 6 months and 14 years subject to eligibility. Despite several government interventions, average calorie intake has declined even as real monthly expenditure has increased, resulting in nutritional deprivation (Basole and Basu, 2015; Deaton and Drèze, 2009). These critical situations related to malnutrition and food insecurity render them as two significant public health issues that India is currently facing.

3 Data

3.1 The Young Lives Survey

The data for our paper comes from the Young Lives Survey (YLS). The YLS is a longitudinal cohort study to examine the determinants of childhood poverty in four countries: Ethiopia, India, Peru and Vietnam(Galab et al., 2003). This paper specifically focuses on the Indian sample of YLS conducted in Andhra Pradesh (AP). AP is one of the largest states in India and as of 2011, it had a population of over 84 million inhabitants. It is categorized into the three regions of Coastal Andhra, Rayalaseema, and Telangana. It is further divided into districts and sub-districts (mandals) with these sub-districts serving as the primary sampling units for data collection (see, http://www.younglives.org.uk for details). AP was bifurcated into two states named as AP and Telangana in June, 2014. Since then the YLS has continued in both the states. We refer to these two states as AP in the paper sinc,e the YLS initiated the data collection in united AP in 2002.

YLS collected extensive information on 2,011 children aged between 6 and 21 months (Younger Cohort or YC) and 1,008 children aged between 7.5 and 8.5 years (Older Cohort or OC) for the first survey round in 2002. Subsequent data collection occurred in 2006-07, 2009-10, 2013-14 and 2016-17. Our analysis uses data from rounds 2 to 5 for the YC, when children were aged around 5, 8, 12, and 15 years, and rounds 2 and 3 for the OC, when children were aged around 12 and 15 years. We exclude the first (2002) round of data for both the cohorts and fourth (2013-14) and fifth (2016-17) rounds of data for the OC as information of household food insecurity was not collected for them in these rounds.

3.2 Explanatory Variable of Interest

The explanatory variable of interest is household food insecurity. YLS measures household food insecurity through experience-based scales (Aurino and Morrow, 2018). Initially, these scales were used in the US (Bickel et al., 2000) and were later adapted and validated in the less- and middle-income countries (Ballard et al., 2013). In YLS, the child's caregiver responds to questions related to the food situation in the households during the past 12 months. A six-item adaptation of the US Household Food Security Measure is used in the round 2 (Bickel et al., 2000). A household is considered food insecure if the caregiver responds affirmatively to either of the following food insecurity questions of - limiting portion size, skipping meals, skipping food for a whole day, borrowing food or money to buy food or any household member forfeiting meals for other household members. Rounds 3, 4, and 5 use the Household Food Insecurity Access Scale (HFIAS) to measure the household food insecurity. The HFIAS is based on the idea that the experience of food insecurity (access) causes predictable reactions and responses that can be captured and quantified through a set of questions and summarized on a scale (see Table A1). Follow-up questions were asked to track the reoccurrence of these events in the last 12 months.

Following the strategy of Coates et al. (2007), we use the basic questions along with the follow-up questions on frequency and categorize the households into four levels of food insecurity as follows: (i) food secure – no experience of food insecurity conditions or rarely worried about running out of food; (ii) mildly food insecure – the household worried about running out of food sometimes or often, and/or unable to consume desired food, and/or consume a less varied diet than desired and/or consume undesired food, but only rarely; (iii) moderately food insecure – sacrificed food quality (for instance - consumed less varied diet or undesired food) sometimes or often, and/or reduce portion size or number of meals, rarely or sometimes; (iv) severely food insecure – reduce portion size or number of meals often, and/or experience any of the three most severe conditions (no food to eat, slept hungry or skipped food for a whole day or night), even if rarely. To reconcile the difference in the food insecurity measurement tools used in round 2 relative to remaining rounds 3, 4 and 5, we follow Humphries et al. (2015) and convert the four-category household food insecurity variable into a binary variable. We consider a household as food insecure if it is moderately or severely food insecure as per the HFIAS used in rounds 3, 4 and 5. Hence, food insecurity takes a value one if the household has been food insecure in the last 12 months, and takes a value zero otherwise.

3.3 Main Outcomes

Our main outcome variables are two widely used anthropometric indices for nutrition surveillance: height-for-age z-score (HAZ) and weight for age z-score (WAZ). YLS collects height and weight measurements across all the rounds. YLS calculates HAZ with the help of the statistical package SPSS Macro for the growth standards available at the World Health Organization website. We calculate WAZ in reference to the 2000 CDC growth charts in STATA 16 using the zanthro command (Vidmar et al., 2004). Z-scores are the deviation of the particular anthropometric indicator (such as height or weight) for an individual from the mean value of the reference population divided by the standard deviation of the reference population. For instance, -2.3 as the WAZ for a particular child indicates that the child's weight is 2.3 standard deviations below the mean weight of the reference population. Hence, higher (lower) values of the z-score indicate higher (lower) values of the anthropometric outcome.

3.4 Covariates

We use gender, father's education (whether the child's father has attained formal education or not), mother's education (whether the child's mother has attained formal education or not), mother's height (in cm), number of family members in the household, religion (whether the child belongs to Hindu religion or other religion), ethnicity (whether the child belongs to Scheduled Caste, Scheduled Tribe, Other Backward Class or Other Caste), wealth status (five quantiles indicating the poorest, poor, middle, rich or richest group are created from the wealth index provided by the YLS), residence (whether the household's resides in a rural or urban area) and district level dummies as our covariates. We take variables such as child's gender, father's education, mother's education, mother's height, religion, and ethnicity from round 2. These variables are assumed to be time-invariant as information on these variables is not available in every round.

3.5 Analytical Sample

Our analytical sample consists of 1783 children belonging to YC across every round from 2 to 5. In addition, our sample also consists of 890 children belonging to OC in rounds 2 and 3. These are the children who have non-missing and valid information for the outcome variables, independent variable of interest and covariates. Our main analysis based on the pooled sample consists of 8912 observations.

Table 1 presents the descriptive statistics of the study sample by round and cohort. Mean WAZ shows an improvement for the children belonging to YC from round 2 to 5. Specifically, mean WAZ increases from -2.07 standard deviations in round 2 to -1.63 standard deviations in round 5. While, mean HAZ indicates an improvement from round 2 (-1.64 standard deviations) to round 3 (-1.43 standard deviations), it remains almost the same in rounds 4 and 5. For the OC, we observe a similar pattern in WAZ. Mean WAZ increases from -1.87 standard deviations in round 2 to -1.84 standard deviations in round 3. On the contrary, the mean HAZ decreases from -1.50 standard deviations in round 2 to -1.61 standard deviations in round 3 for the OC.

Our independent variable of interest, the food insecurity indicator, suggests that 8% (9%) of the children belonging to YC (OC) report household food insecurity in round 2. The prevalence of household food insecurity is observed in 30% (27%) of the children belonging to YC (OC) in round 3. While it has declined in the last two rounds, more than 20% of the children belonging to YC continue to experience household food insecurity in rounds 4 and 5.

In terms of the demographics, 54% of children belonging to YC are male, 64% (46%) of children have father (mother) who participated in formal education, average mother's height is 151.46 cm, 92% of them are Hindu, 48% (31%) of them are from Other Backward Class

(Scheduled Caste and Scheduled Tribe), the average family size is over 4, and more than 73% of them live in rural areas. For the children belonging to OC, we observe similar summary statistics. 50% of the children are male, 56% (36%) of children have father (mother) who participated in formal education, average mothers' height is 150.77 cm, 50% (30%) of them are from Other Backward Class (Scheduled Caste and Scheduled Tribe) and the average family size is over 5.

Figure 1 plots the mean WAZ and HAZ with respect to the survey year by status of household food insecurity. It indicates that children belonging to food secure households have higher WAZ and HAZ as compared to their counterparts belonging to food insecure households across all the waves of the YLS. This is suggestive of a negative effect of food insecurity on children's and adolescents' health.

4 Empirics

4.1 Average Effects

The starting point of our analysis is the following OLS estimation:

$$Y_{icdt} = \alpha + \beta FIS_{icdt} + \gamma X_{icdt} + \varepsilon_{icdt} \tag{1}$$

where Y_{icdt} denotes the outcome of interest (WAZ or HAZ) of child i of cohort c residing in district d at time t; FIS_{icdt} denotes an indicator variable equal to 1 for children in food insecure households and 0 otherwise; X_{icdt} denotes the vector of covariates; and ε_{icdt} denotes unobserved individual level determinants of Y_{icdt}. The parameter of interest is β which captures the mean effect of food insecurity, i.e., the effect of food insecurity on WAZ/HAZ for the average child.

A problem with the estimation of Eq. (1) in our study is that FIS_{icdt} could be endogenous on account of multiple unobserved variables that might be correlated with both FIS_{icdt} and Y_{icdt}. Additionally, the effect of covariates on the outcomes might be nonlinear. These problems would render the OLS estimate of β to be biased and inconsistent. Our strategies to address the endogeneity and misspecification problems include selecting a comprehensive set of controls for individuals, households, geographic location; applying propensity score matching and inverse propensity score weighting methods; and comparing the effects of selection on observables with selection on unobservables. These strategies are discussed in more detail below.

Given that we have a panel data, in theory, we could have included child/individual fixed effects to capture the time invariant unobservables. However, we do not include child fixed effects due to very little variation in FIS_{icdt} within a child over time. Close to 75% of the children in the OC have no variation in their food security status over time. For the YC, this figure is around 50%. As such, including individual fixed effects would mean excluding a large proportion of the sample. This in turn would likely result in severe sample selection bias. As noted in (Longhi and Nandi (2014), p.189), when covariates of interest or predictor variables are characterized by little variation over time "coefficients of these variables are identified by a very small number of observations (individuals) and may not be very reliable."[4]

4.1.1 Comprehensive Controls

When the data is rich enough, it can be argued that the effects of unobservable factors can be mitigated (although not eliminated) by controlling for all of the theoretically-relevant observables. Fortunately, the YLS contains very rich information about the child, the household, and the neighborhood. We test the effects of exploiting the richness of the dataset by comparing the estimated parameters of interest (β) in the "basic" and "comprehensive" specifications. In the "basic" specification, we only control for the child's cohort, residential district and the year of the survey. In addition to these aforementioned variables, the comprehensive specification also includes the gender of the child, father's education, mother's education, mother's height, family size, wealth index, religion, caste, and whether the household is living in a rural or urban area. All these variables could potentially be correlated with both household security status and children's health.

4.1.2 Propensity Score Matching

As in regression-based techniques, propensity score matching relies on the assumption of "selection on observables": conditional on observable characteristics, children in food secure and food insecure households do not systematically differ along unobservable dimensions. The primary advantage of the propensity score approach is that it is robust to misspecification of the regression model given by (1). This approach does not rely on linearity of effect of covariates on the outcome in order to generate consistent estimates of treatment effects.

We specify the propensity score as follows:

$$FIS_{icdt} = \mathbb{I}(f(X_{icdt}) + \upsilon_{icdt} > 0) \tag{2}$$

where $\mathbb{I}(\cdot)$ denotes the indicator function that takes on the value 1 if its argument is true and zero otherwise, $f(X_{icdt})$ denotes a flexible function of all of the elements of X_{icdt}, and υ_{icdt} denotes unobserved determinants of food insecurity.

In the analysis below, we estimate the propensity scores based on probit models, but we assess the sensitivity of the estimates to the assumed distribution of υ_{icdt} by also using logit models. Although propensity scores are widely used in the matching literature, no single method can be considered to be the 'best' (see, e.g., Frölich (2004)). Therefore, we employ two commonly-used matching methods: kernel density and k-nearest neighbor. The kernel density estimator compares each child in the treatment group (in our case, child in food insecure households) to a weighted average of all comparison group observations, with the weight for each observation in the comparison group inversely proportional to the difference between that observation's estimated propensity score and the propensity score of the treatment child (we use an Epanechnikov kernel with a bandwidth of 0.08 as recommended by Silverman (1986)). In the k-nearest neighbor approach, each child in the treatment group is matched with k children in control group who have the most similar propensity scores. In the k-nearest neighbor estimator, we use three alternative values of k, viz, $k = 1, 3$, and 5.

As we show below, our main conclusions are insensitive to not only the smoothing parameters we choose for a given method, but to the method itself – estimates based on the kernel density and nearest neighbor methods are similar in all cases.

4.1.3 Inverse Propensity Score Weighting Estimator

The inverse propensity score weighting (IPW) estimator proposed by Hirano et al. (2003) is an alternative to matching estimators, but relies on estimating the propensity score. In calculating the treatment effects, the estimator weights observations by the inverse of nonparametric estimates of the propensity score, rather than the true propensity score. For participants in a treatment arm, a weight of $w_i = 1/\widehat{P}_i$ is assigned, while participants in a control arm are assigned weights of $w_i = 1/(1 - \widehat{P}_i)$, where $\widehat{P}_i$ is the estimate of the propensity score. The intuition behind the IPW estimator is simple. Individuals who were assigned to the treatment group even though they were much more likely to be assigned to the control group are a rare, and valuable group. We want to give their outcomes as much weight as possible, whereas the much larger group of individuals who were placed in the control group need less weight, simply because we have much more information on individuals like this. Extending results from Newey (1994) to derive the large sample properties of this semiparametric estimator, Hirano et al. (2003) show that it achieves the semiparametric efficiency bound. Further the IPW estimator requires fewer functions to be estimated nonparametrically than other matching estimators.

4.1.4 Selection on Observables and Unobservables

In order to evaluate whether omitted variables drive the OLS and matching results, we adopt a technique developed in Oster (2019). This method is based on the Altonji et al. (2005) idea that selection on observables can provide a useful guide to assess the selection based on unobservables. To elaborate further, consider Eq. (1). where FIS_{icdt} is the independent variable of interest, X_{icdt} is observed and ε_{icdt} contains all the unobserved components. The objective is to estimate the bias on β because of ε_{icdt}. Altonji et al. (2005) estimate this bias by assuming the following:

$$\frac{Cov(FIS_{icdt}, \varepsilon_{icdt})}{V(X_{icdt})} = \delta \frac{Cov(FIS_{icdt}, \gamma X_{icdt})}{V(\gamma X_{icdt})} \tag{3}$$

In other words, the relation of FIS_{icdt} and unobservables is proportional to the relation of FIS_{icdt} and observables, the degree of proportionality given by δ. This basic insight has been extended by Oster (2019). In her approach, in addition to δ, another parameter specifies the relationship between observable and unobservable selection and the maximum amount of variation that can be explained by the model. This parameter is R_{max}, the maximum R-squared under the full model in Eq. (1) where all (observed and unobserved) variables are included. Both δ and R_{max} are unknown parameters to be chosen given the particular context of the problem and econometric model. There are no standard values but Oster (2019) argues that an appropriate upper bound for δ is 1 because the observed variables are usually chosen based on the fact that they are the most important controls. Conceptually we can think of the omitted variables as having been stripped of the portion related to the included variables (Oster, 2019). The range 0 to 1 for δ seems reasonable in our context, as we observe the key control variables that have been identified in the literature on health and food security. The bound when $\delta = 0$

is $\widetilde{\beta}$ (the estimate from the controlled regression). The other bound, β^*, can be approximated by the expression:

$$\beta^* = \widetilde{\beta} - \delta[\dot{\beta} - \widetilde{\beta}]\frac{R_{\max} - \widetilde{R}}{\widetilde{R} - \dot{R}}$$

where $\dot{\beta}$ is the estimate of β from the uncontrolled regression (i.e., the regression that does not include any controls), $\widetilde{R}$ and $\dot{R}$ are the R-squared values from the controlled and uncontrolled regressions respectively (see Oster (2019) for more details).

To operationalize this method, one needs to posit R_{max}. One way to do this is to look at R-squares obtained in other studies in the same context that control reasonably well for the omitted variables, and set R_{max} as the average of R-squares of those studies. Alternatively, one can follow Oster (2019)'s suggestion and set R_{max} as 1.3 times the R-square of the regression that controls for X_{icdt} (controlled regression). This suggestion is based on Oster (2019) analysis using a sample of randomized papers (from top journals). She shows that the value of R_{max} which allows at least 90% of randomized results to survive randomized papers is 1.3 $\widetilde{R}$. Given the paucity of such studies that control reasonably well for omitted variable bias in context of India, we cannot adopt the first approach. Instead we proceed with the second approach and set $R_{max} = 1.3\ \widetilde{R}$. However, we also check the sensitivity of our results to two other values in neighborhood of 1.3 $\widetilde{R}$, viz, 1.1 $\widetilde{R}$ and 1.5 $\widetilde{R}$.

This approach allows us to compute a bounding set Δ_s with the following bounds $[\widetilde{\beta}, \beta^*(\min(R_{max}, 1), \delta)]$. The baseline results can be considered to be robust if the bounds do not include zero. We implement this approach in Stata 16 using PSACALC (Oster, 2016).

4.2 Distributional Effects

The estimators discussed above focus on the estimation of the average effect. However, solely focusing on the average effects might cause us to miss interesting heterogeneity in the treatment effects. As such, we move beyond the mean effects in order to examine the impact on the entire distribution of the outcomes using QTE models. QTEs allow us to understand how food insecurity changes the trajectory of health outcomes distribution, i.e., whether most of the changes in health outcomes of the children between the food insecure and secure households are in the tails, in the middle or throughout the distribution.

In what follows, we briefly outline two widely used QTE estimators: conditional QTE estimator and unconditional QTE estimator. In outlining these estimators, we use a potential outcomes framework where Y^1_{icdt} and Y^0_{icdt} denote the potential outcomes of individual i. Hence, Y^1_{icdt} would be realized if child i were to receive treatment 1 (child lives in a food insecure household), and Y^0_{icdt} would be realized otherwise.

4.2.1 Conditional QTE

The conditional QTE rests on two fundamental assumptions. First, Y is a linear function in X and FIS. That is

$$Y^q_{icdt} = X_{icdt}\gamma^\tau + q\beta^\tau + \varepsilon^\tau_{icdt} \text{ and } Q^\tau_{\varepsilon_{icdt}} = 0 \tag{4}$$

for $i = 1, 2, ..., n$ and $q \in (0, 1)$. $Q^\tau_{\varepsilon_{icdt}}$ refers to the τth quantile of the unobserved random variable ε_{icdt}. γ^τ and β^τ are the unknown parameters of the model. Here β^τ represents the conditional QTEs at quantile τ. Second, we assume that both FIS_{icdt} and X_{icdt} are exogenous.

These two assumptions together imply that $Q^\tau_{Y \mid FIS, X} = FIS_{icdt}\beta^\tau + X_{icdt}\gamma^\tau$, such that we can recover the unknown parameters of the potential outcomes from the joint distribution of the observed variables Y, X and FIS. The unknown coefficients can thus be estimated by the classical quantile regression estimator suggested by Koenker and Bassett Jr (1978). This estimator is defined by

$$(\widehat{\beta}^\tau, \widehat{\gamma}^\tau) = \arg\min_{\beta,\gamma} \sum \rho_\tau(Y_{icdt} - X_{icdt}\gamma - FIS_{icdt}\beta) \tag{5}$$

where $\rho_\tau(u) = u \times \{\tau - 1(u < 0)\}$. This is a convex linear programming problem which can be solved using any standard software package.

4.2.2 Unconditional QTE

The estimator presented above focuses on conditional treatment effects, that is, conditional on a set of variables X. A drawback of the conditional QTEs is its limited scope of interpretation due to its conditionality on observations sharing similar covariates values (Bosio, 2014).[5] To overcome this limitation, an estimator to estimate unconditional QTEs is proposed.

The unconditional QTE (for quantile τ) is given by

$$\Delta^\tau = Q^\tau_{Y^1} - Q^\tau_{Y^0} \tag{6}$$

Unlike conditional QTEs, the definition of the unconditional QTE does not change when we change the set of covariates X. Although we aim to estimate the unconditional effect, we still use the covariates X for two reasons. First, the usage of covariates makes the identification assumptions more plausible. Second, covariates increase efficiency. Therefore, covariates X are included in the first-step regression and then integrated out. However, the definition of the effects is not a function of the covariates.

Identifying the unconditional QTE requires us to assume that X contains all confounding variables, which we denote as the selection on observables assumption. We also have to assume that the support of the covariates is the same independent of the treatment, because in a nonparametric model, we cannot extrapolate the conditional distribution outside the support of the covariates. These assumptions allow us to identify the unconditional QTE (Firpo, 2007; Frölich, 2007; Melly, 2006) using the following weighting estimator for Δ^{τ}:

$$
\begin{aligned}
(\widehat{\alpha}, \widehat{\Delta}^{\tau}) &= \arg\min_{\alpha,\Delta} \sum W_i^F \times \rho_{\tau}(Y_{icdt} - \alpha - FIS_{icdt}\Delta) \qquad (7) \\
W_{icdt}^F &= \frac{FIS_{icdt}}{P(FIS_{icdt}=1|X_{icdt})} + \frac{1-FIS_{icdt}}{1-P(FIS_{icdt}=1|X_{icdt})}
\end{aligned}
$$

This is a traditional propensity-score weighting estimator. A preliminary estimator for $P(FIS_{icdt} = 1|X_{icdt})$ is needed to implement this estimator. We use the local logit estimator for this purpose.

Note, while we estimate QTEs using both the above methods, in the present application, the results for unconditional QTE are likely to be more important than the results for the conditional QTE from a policy view point. This is because in contrast to conditional QTE (i.e., the effects conditional on a large number of covariates X), the unconditional QTE summarize the effects of a treatment for the entire population (Frölich and Melly, 2013) which is likely to be of most interest in policy evaluations.

5 Results

5.1 Average Effect

The results of our analysis pertaining to the average effect of household food insecurity on WAZ and HAZ are presented in Tables 2-6. Table 2 presents the OLS estimates. The table consists of three panels. The first panel presents the results based on the naive specification, i.e., the specification that does not include any control variable. Results in the second panel are based on the regressions that use basic controls including cohort fixed effects, district fixed effects and survey year fixed effects. The third panel presents the results of the regressions which include the basic controls plus controls for child's gender, father's education, mother's education, mother's height, family size, wealth dummies, religion, caste and a dummy indicating whether the household is living in a rural or urban area. In each panel, along with the results for the full sample, we present the results for subsamples consisting of rural and urban households separately.

We start by looking at the impact of food insecurity on WAZ and HAZ based on the naive specification (Panel I). For the full sample, the coefficient of food insecurity from the regression that uses WAZ as the dependent variable is -0.30 and that from the regression that uses HAZ as the dependent variable is -0.23. Both these coefficients are statistically significant at 1% level of significance. This suggests that, absent any controls, WAZ (HAZ) of children belonging to food insecure households are 0.30 SD (0.23 SD) lower than the WAZ (HAZ) of children belonging to food secure households. The results based on the rural and urban samples for the naive specification are in line with the full sample results (i.e., the estimated coefficients are negative and statistically significant), although the negative effect of food insecurity on the anthropometric measures is stronger for the urban sample than the rural sample.

The regressions that use the basic controls (Panel II) do not produce results that are very different from the naive regressions. For the full sample, the effect of food insecurity on WAZ reduces only slightly, while the effect of food insecurity on HAZ remains almost unaltered. Specifically, for the full sample, with basic controls, our results indicate that WAZ (HAZ) of children who belong to food insecure households are 0.26 SD (0.22 SD) lower than the WAZ (HAZ) of children who belong to food secure households. Turning to the results for the subsamples, we find that inclusion of the basic controls reduce the effect of food insecurity on WAZ (from 0.20 SD to 0.18 SD) and increases the effect of food insecurity on HAZ slightly (from 0.15 SD to 0.16 SD) for the rural sample. For the urban sample, on the other hand, inclusion of the basic controls increases the effect of food insecurity on both WAZ (from 0.27 SD to 0.34 SD) and HAZ (0.26 SD to 0.31 SD).

Our preferred specification is the one that uses the comprehensive set of controls (Panel III). This specification controls for several variables which could potentially be confounding the effect of food insecurity on WAZ and HAZ. For the full sample as well as for the urban and rural samples, while the magnitudes of the coefficients of food insecurity under this specification are smaller than the magnitudes of coefficients under the basic controls specification (in absolute terms), they continue to remain economically and statistically significant. The estimated coefficients of food insecurity under the comprehensive controls specification suggest that, for the full sample, WAZ (HAZ) of children who belong to food insecure households is 0.10 SD (0.07 SD) lower than the WAZ (HAZ) of children who belong to food secure households. For the rural and urban samples, WAZ (HAZ) of children who belong to food insecure households is 0.07 SD (0.05 SD) and 0.13 SD (0.14 SD) lower than the WAZ (HAZ) of children who belong to food secure households respectively. These results indicate that even after accounting for the observable differences between food insecure and food secure households, there exists a significant negative relationship between food insecurity and children's anthropometric indices of nutritional surveillance. Further, the negative effect of food insecurity on these anthropometric measures for the urban households is 2-3 times greater than that for the rural households.

Table 3 presents the propensity score matching-based estimation results. The table consists of two panels. Panel I presents the propensity score matching estimates using the kernel method and the second panel using the k-nearest neighbor method. For both methods, we use the comprehensive set of controls to compute the propensity scores and compare the anthropometric indices of nutritional surveillance of children. The matching results, in line with the OLS results, point to a strong negative relationship between food insecurity and WAZ and HAZ. The effects are larger for WAZ than HAZ. The estimated effects are statistically significant and larger than the corresponding OLS estimates. For example, the Kernal matching estimates (Panel I) for the full sample suggest that WAZ (HAZ) of children who belong to food insecure households is 0.18 SD (0.17 SD) lower than the WAZ (HAZ) of children who belong to food secure households. The results for k-nearest neighbor matching estimates (Panel II) for the full sample are very similar to the kernel matching results. When the matching methods are carried out separately for the urban and rural samples, we continue to find evidence of negative and statistically significant effect of food insecurity on WAZ and HAZ. Further, like the OLS regression with comprehensive controls, we find that across all the matching methods, the effect of food insecurity on HAZ and WAZ is substantially stronger for the urban sample than the rural sample. For example, using the nearest neighbor matching method (i.e., $k = 1$), while the estimated treatment effect for WAZ and HAZ are -0.18 and -0.17 respectively for the rural sample, the corresponding effects for the urban sample are -0.33 and -0.25.[6]

The inverse propensity score weighted estimation results are presented in Table 4. These results are also consistent with the OLS and the propensity score matching results with comprehensive controls. In particular, the inverse propensity score weighted estimates indicate that, for the full sample, WAZ (HAZ) of children who belong to food insecure households is 0.19 SD (0.17 SD) lower than the WAZ (HAZ) of children who belong to food secure households. For the rural and urban samples, WAZ (HAZ) of children who belong to food insecure households is 0.15 SD (0.14 SD) and 0.25 SD (0.23 SD) lower than the WAZ (HAZ) of children belonging to food secure households respectively.

In short, the results from OLS, propensity score matching estimation and inverse propensity score weighted estimation suggest that household food insecurity has a significant negative effect on children's health as measured by the anthropometric indices of nutritional surveillance. These three estimators mainly rely on the richness of the YLS data to militate against the probable effect, otherwise, of unobserved heterogeneity. Nevertheless, we cannot rule out a role for unobserved heterogeneity. Thus, we also apply the "selection on unobservables versus observables" approach by Oster (2019), that can determine the range of estimate of parameters (or treatment effects) when the proportion of selection on unobservables and selection on observables increases from 0 through 1. We report the results of this exercise in Table 5. The results for the full sample are in the first panel and, for the rural and urban subsamples in the second and the third panels respectively. In each panel, we let δ, which shows how strongly the unobservables drive treatment assignment relative to the observables, to vary from 0.25 to 1 ($\delta = 0$ would imply no selection on unobservables), and for each value of δ, we compute the bounds within which the "true" effect of food insecurity on WAZ and HAZ would lie, for a given value of R_{max}. As discussed in Section 4.4, we use three values of R_{max}, $1.1\widetilde{R}, 1.3\widetilde{R}$,and $1.5\widetilde{R}$.

The estimated bounds on the "true" effect of food insecurity on WAZ suggest that for the full sample as well as for the urban and rural subsamples, if the degree of selection on unobservables is 75% of the degree of selection on observables, the effect of food insecurity on WAZ is negative irrespective of the value of R_{max} considered. In fact, even if the degree of selection on unobservables is as much as that of selection on observables, the effect of food insecurity on WAZ is always negative for the urban sample, and the effect of food insecurity on WAZ is negative for the full sample and rural sample if $R_{max} = 1.3\widetilde{R}$ (or lower) (recall that as shown by Oster (2019), the value of R_{max} which allows at least 90% of randomized results to survive randomized papers is $1.3\widetilde{R}$).

Turning to the estimated bounds on the "true" effect of food insecurity on HAZ, we find that for the full sample (urban and rural samples), if the degree of selection on unobservables is 50% (75%) of the degree of selection on observables, the effect of food insecurity on HAZ is negative irrespective of the value of R_{max} considered. Even if the degree of selection on unobservables is as much as that of selection on observables, the effect of food insecurity on HAZ is always negative for the urban sample, and the effect of food insecurity on HAZ is negative for the full sample and rural sample if $R_{max} = 1.3\widetilde{R}$ (or lower). Overall, these bounds, thus, provide evidence that our main findings are robust to sufficiently high degrees of selection on unobservables. Put differently, these bounds confirm that children belonging to food insecure households have significantly lower WAZ and HAZ than children belonging to food secure households, *ceteris paribus*.

Heterogeneity Analysis To examine whether our main results vary across different subsamples, we cut our analytical sample in different ways and estimate the effect of food insecurity on WAZ and HAZ for these subsamples using the OLS method with comprehensive controls. The results are presented in Table 6. Before discussing the results, it is worth noting that while many estimated coefficients in Table 6 are not statistically significant at the conventional levels of significance, they are economically significant (e.g., the effect of food insecurity on WAZ and HAZ for the children belonging to the older cohort). As such, we refrain from interpreting these coefficients as providing evidence of absence of relationship between food insecurity and WAZ/HAZ.

The following findings are noticeable in our heterogeneity analysis. First, the negative effects of food insecurity on WAZ and HAZ are stronger for the younger cohort of children in the YLS than for the older cohort. Second, compared to children belonging to Other Backward Class and Scheduled Caste/Scheduled Tribe households, the negative effects of food insecurity on WAZ and HAZ are remarkably higher for children belonging to upper caste households. Third, the adverse effects of food insecurity on the anthropometric measures are stronger for children belonging to Hindu households than households following other religions (in fact, the effect of food insecurity on HAZ for children belonging to other religions is almost zero). Finally, compared to children in households belonging to the bottom 50% of the wealth distribution, the negative effect of food insecurity on WAZ and HAZ is remarkably higher for children in households belonging to the top 50% of the wealth distribution. These results collectively indicate presence of some heterogeneity in the estimated relationship between food insecurity and children's anthropometric measures.

5.2 Distributional Effects

The results discussed above suggest that, on average, food insecurity has a negative effect on children's WAZ and HAZ. But does this affect vary across the distributions of children's WAZ and HAZ? To answer this question, we turn to the estimates of conditional and unconditional QTEs. We estimate the conditional and unconditional QTEs at 11 percentiles (1, 10, 20, 30, 40, 50, 60, 70, 80, 90, and 99) for both WAZ and HAZ. The QTE estimates along with 95% confidence bounds are presented in Figures 2–5.

We start by looking at the conditional QTE estimates of food insecurity on WAZ and HAZ (Figure 2 and 3). For the full sample, we observe that estimated conditional QTE of food insecurity on WAZ is negative across all the percentiles ranging between -0.03 to -0.27. In terms of absolute magnitude, the estimated effect seems to be higher in the upper tail of the distribution (beyond the 70th percentile) than in the lower tail (between 10th and 50th percentile), with it being largest at the 99th percentile. For HAZ, the estimated conditional QTE is negative across all the percentiles except the first; the estimated effects lie between 0.01 (1st percentile) and -0.12 (50th percentile). However, most of the QTEs are estimated imprecisely.[7] Turning to the subsample results for the conditional QTEs, we find that for WAZ, except for the 1st and 10th percentile, the negative effect of food insecurity is stronger for children belonging to households in urban areas than children belonging to households in rural areas. For HAZ, the results are slightly different: except for children belonging to the 90th percentile of the HAZ distribution, the adverse effect of food insecurity on HAZ is always relatively stronger for children belonging to households in urban areas.

We next turn to the results for unconditional QTEs (Figures 4 and 5), which, as noted previously, is likely to be more useful from a policy point of view. For the full sample, we find that the estimated unconditional QTEs of food insecurity on WAZ range between -0.53 and -0.06. In absolute terms, estimated unconditional QTEs of food insecurity on WAZ is lowest at the 10th percentile and highest at the 99th percentile. Between the 10th and the 99th percentile, we observe that estimated QTE (in terms of absolute magnitude) shows a clear increasing trend as one moves from the lower percentiles towards the upper percentiles. For

HAZ, the unconditional QTEs range between -0.16 (1st percentile) and -0.28 (90th percentile). Further, like WAZ, in absolute terms, the estimated QTE exhibits an increasing trend as one moves from lower towards the upper percentiles of the distribution. The results based on the subsamples for the unconditional QTE show no evidence of difference in impact of food insecurity on WAZ and HAZ by whether a child belongs to an urban or rural household.

In sum, thus, what can be concluded based on the estimates of the QTEs is that although food insecurity adversely affects health of children across the distribution of WAZ and HAZ, there is considerable variation in the effect. In particular, the effect of food insecurity on health of children is likely to be more severe for children belonging towards the upper end of the WAZ/HAZ distribution than those belonging towards the lower end.[8] This is a particularly noteworthy finding. While ascertaining the exact cause of this finding is beyond the scope of the present research, we believe this could be possibly because children who belong to the lower end of the health distribution come from relatively more disadvantageous backgrounds and therefore have access to government schemes which allow them to partially mitigate the adverse effects of food insecurity.[9] This, in turn, might cause their health to be affected less adversely by household food insecurity than their counterparts.

In fact, this might also be a possible explanation of why we previously find the average adverse effect of food insecurity on child health to be higher for children living in urban households, children belonging to upper caste and non-minority households, and children from relatively less poor households compared to their counterparts. To the extent that most urban, upper caste, non-minority and relatively less poor households have limited or no access to government schemes and safety nets like their counterparts (since they are not likely to be perceived to be in severely disadvantageous position), they have no means, unlike their counterparts, to mitigate the adverse effects of household food insecurity.

6 Conclusion

Food insecurity emerges as an important determinant of malnutrition throughout our analysis. All our empirical strategies including propensity score matching, inverse propensity weighting estimator and comparisons of selection on unobservable and observable estimators, indicate consistently negative average effects of food insecurity on children's anthropometric indices for nutrition surveillance. This is seen for the full sample as well as the rural and urban subsamples. We also note some interesting heterogenous and distributional effects of food insecurity on children's anthropometric measures. For example, we find that the adverse effect of food insecurity on health of children is likely to be more pronounced for children belonging to urban areas, those belonging to upper caste and non-minority households, those belonging to relatively non-poor households and those who belong towards the upper end of the health distribution than their counterparts.

The issue addressed in this paper is timely and relevant not only considering India's nutritional targets of 2022 (NNM 2022) but also because the challenges of the COVID-19 crisis are likely to deteriorate the already critical situation India faces in terms of malnourishment. Our findings suggest that expansion of policies that could effectively reduce food insecurity is important to address the problem of malnutrition among Indian children. A policy driven reduction in food insecurity is especially paramount if India is to reap the benefits of its demographic dividend and aim for improved productivity of its future labor force.

Our findings call for greater focus on nutritional support for children under the umbrella of the National Food Security Act. Specifically, improvements in the indicators of malnutrition would require effective improvements in the functioning of the ICDS and the Mid-Day Meal Scheme (MDMS) considering the large impacts these schemes have had on the nutrition of children especially in times of economic distress (Jain, 2015; Mittal et al., 2015; Afridi, 2010; Singh et al., 2014; Dhamija and Sen, 2021). In addition, interventions that create safety nets to protect households against income shocks can play a key role.

Our findings also suggest that policymakers in India should not only focus on households that are conventionally thought to be in most disadvantageous positions (e.g., rural households, lower caste/minority households, households living below the poverty line, etc.) when it comes to ensuring access and affordability of a balanced diet for children. Our results show that, if anything, food insecurity has a greater adverse effect on children belonging to relatively less disadvantageous households than their counterparts. To address the problem of malnutrition in India, therefore, creating opportunities for food systems to increase the supply of affordable and nutritious foods for children across the spectrum is likely to be crucial.

Our findings should be read with two caveats. First, our findings in no way suggest that to tackle the problem of child malnutrition in India focusing entirely on enhancing the food security is likely to be sufficient especially because the estimated magnitudes of at least the direct effect of food insecurity on malnutrition are not very large. Food insecurity is an important determinant of child malnutrition but the pathogenesis of malnutrition is multifactorial and there is a multiplicity of etiologies of nutritional status. Thus, as noted by (Tiwari et al., 2013), food security policies must be considered a pathway instead of an end to deal with the problem of malnutrition. It is important for the policymakers and developmental practitioners to recognize this so as to avoid forming unrealistic expectations about what policies enhancing food security can achieve. Second, despite using several econometric techniques to examine the effect of food insecurity on child malnutrition, we cannot claim that our results are causal. For obtaining causal results, one needs to employ experimental or quasi-experimental research methodology. We hope future work will address this issue.

Notes

[1]This might, however, not seem to be very unusual if one looks at the overall food security literature since, in general, studies in this literature that focus on children (especially those who are school-aged) and adolescents are scarce (Aurino and Morrow, 2018). In fact, as noted by Hadley et al. (2009), these population groups are often referred to as the "forgotten population" in the food security literature.

[2]It is worth noting in this context that it is not the case that the findings are mixed only for India. Chandrasekhar et al. (2017) and Pathak et al. (2020) clearly note that, in general, findings from the studies that examine the association between indicators of child undernutrition on one hand and indicators of child dietary intake and household food security on the other are far from robust.

[3]In particular, insufficient weight gain during pregnancy through intrauterine growth restriction increases the risk factor for stunting of children, which is a grave issue in India.

[4]Note, even if the independent variable of interest has little or no variation over time (as a result of which we cannot include fixed effects), there is a benefit of using panel data. Panel data usually increases the sample size and contain more degrees of freedom than cross-sectional data which may be viewed as a panel with $T = 1$, or time series data which is a panel with $N = 1$, hence improving the efficiency of econometric estimates (Hsiao, 2007). In other words, panel data is likely to result in more precise estimates.

[5]While conditioning on a set of observed regressors does not affect the interpretation of the parameters in a mean regression, this is not the case for quantiles. The law of iterated expectations guarantees that the parameters of a mean regression have both a conditional and an unconditional mean interpretation. This does not carry over to quantiles, where conditioning on covariates affects the interpretation of the residual disturbance term. Indeed, since quantile regression allows one to characterize the heterogeneity of the treatment response only along this latter dimension, conditioning on covariates in quantile regression generally affects the interpretation of the results.

[6]In Table A2 in the appendix, we provide matching statistics (how many observations can and cannot be matched) for all the specifications. Further, we provide kernel density plots of propensity scores of the treated and control groups (Figure A1). As evident from Table A2 and Figure A1, the common support assumption is

likely to hold for all the specifications.

[7]This is not surprising since these are conditional QTEs.

[8]For different percentiles, if we compute the unconditional QTE of food insecurity in terms of percentage, that also seems to be rising with percentiles. That is, not only in terms of the SD but in terms of percentage as well, children who belong to at the upper end of the WAZ and HAZ distributions are more severely affected by food insecurity than their counterparts.

[9]As noted by Pingali et al. (2019), indeed, the safety nets provided by the government especially ensure the well-being of the most marginalized (e.g., under the NFSA, while the eligible monthly entitlements include 5 kg of grains per person at subsidized prices, the poorest of the poor receive 35 kgs of food grains per month).

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Table 1. Summary Statistics

	Younger Cohort								Older Cohort			
	Round 2: 5 years old		Round 3: 8 years old		Round 4: 12 years old		Round 5: 15 years old		Round 2: 12 years old		Round 3: 15 years old	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Weight for Age Z-score (WAZ)	-2.07	1.13	-2.06	1.18	-1.78	1.24	-1.63	1.32	-1.87	1.20	-1.84	1.25
Height for Age Z-score (HAZ)	-1.64	0.97	-1.43	1.03	-1.43	1.01	-1.44	0.95	-1.50	1.04	-1.61	0.99
Food Insecure (=1 if yes)	0.08	0.28	0.30	0.46	0.24	0.43	0.25	0.44	0.09	0.29	0.27	0.44
Male (=1 if yes)	0.54	0.50	0.54	0.50	0.54	0.50	0.54	0.50	0.50	0.50	0.50	0.50
Father’s Formal Education (=1 if yes)	0.64	0.48	0.64	0.48	0.64	0.48	0.64	0.48	0.56	0.50	0.56	0.50
Mother’s Formal Education (=1 if yes)	0.46	0.50	0.46	0.50	0.46	0.50	0.46	0.50	0.36	0.48	0.36	0.48
Mother’s height (in cm)	151.46	6.40	151.46	6.40	151.46	6.40	151.46	6.40	150.77	9.93	150.77	9.93
Household Size	5.53	2.20	5.45	2.25	4.90	1.79	4.79	1.70	5.20	1.81	5.06	1.89
Hindu (=1 if yes)	0.92	0.28	0.92	0.28	0.92	0.28	0.92	0.28	0.92	0.27	0.92	0.27
Ethnicity												
Scheduled Caste (=1 if yes)	0.18	0.39	0.18	0.39	0.18	0.39	0.18	0.39	0.20	0.40	0.20	0.40
Scheduled Tribe (=1 if yes)	0.13	0.34	0.13	0.34	0.13	0.34	0.13	0.34	0.10	0.30	0.10	0.30
Other Backward Class (=1 if yes)	0.48	0.50	0.48	0.50	0.48	0.50	0.48	0.50	0.50	0.50	0.50	0.50
Other caste (=1 if yes)	0.21	0.41	0.21	0.41	0.21	0.41	0.21	0.41	0.21	0.40	0.21	0.40
Wealth Status												
Poorest (=1 if yes)	0.20	0.40	0.21	0.40	0.20	0.40	0.20	0.40	0.19	0.39	0.20	0.40
Poor (=1 if yes)	0.20	0.40	0.19	0.40	0.22	0.42	0.20	0.40	0.20	0.40	0.19	0.40
Middle (=1 if yes)	0.21	0.40	0.21	0.40	0.18	0.38	0.20	0.40	0.21	0.41	0.21	0.41
Rich (=1 if yes)	0.20	0.40	0.19	0.39	0.20	0.40	0.20	0.40	0.20	0.40	0.20	0.40
Richest (=1 if yes)	0.20	0.40	0.20	0.40	0.20	0.40	0.20	0.40	0.20	0.40	0.20	0.40
Rural (=1 if yes)	0.75	0.43	0.75	0.44	0.73	0.44	0.73	0.45	0.76	0.43	0.75	0.43
N	1783		1783		1783		1783		890		890	

Table 2. OLS estimates of the effect food insecurity on health outcomes

	WAZ	HAZ
I. No Controls		
Full Sample	-0.300***	-0.229***
	(0.030)	(0.025)
Rural	-0.201***	-0.149***
	(0.033)	(0.027)
Urban	-0.268***	-0.258***
	(0.075)	(0.063)
II. Basic Controls		
Full Sample	-0.259***	-0.215***
	(0.031)	(0.025)
Rural	-0.176***	-0.156***
	(0.033)	(0.027)
Urban	-0.339***	-0.307***
	(0.074)	(0.064)
III. Comprehensive Controls		
Full Sample	-0.096***	-0.070***
	(0.030)	(0.024)
Rural	-0.070**	-0.054**
	(0.033)	(0.027)
Urban	-0.134*	-0.135**
	(0.079)	(0.066)

Notes: Robust standard errors in brackets. “Basic controls” include control for child's cohort, residential district and the year that the survey was conducted. “Comprehensive controls” include the basic controls plus the gender of the child, father’s education, mother’s education, mother’s height, family size, wealth index, religion, caste, and whether the household is living in a rural or urban area.

*** $p < 0.01$.

** $p < 0.05$.

* $p < 0.1$.

Table 3. Propensity score estimates of the effect food insecurity on health outcomes

	WAZ	HAZ
I. Kernel		
Full Sample	-0.182***	-0.172***
	(0.034)	(0.031)
Rural	-0.154***	-0.147***
	(0.037)	(0.032)
Urban	-0.202*	-0.209**
	(0.116)	(0.091)
II. k-Nearest Neighbor		
(a) k = 1		
Full Sample	-0.193***	-0.173***
	(0.056)	(0.043)
Rural	-0.181***	-0.170***
	(0.046)	(0.042)
Urban	-0.329**	-0.246
	(0.159)	(0.150)
(b) k = 3		
Full Sample	-0.201***	-0.180***
	(0.060)	(0.051)
Rural	-0.208***	-0.171***
	(0.051)	(0.042)
Urban	-0.387**	-0.299**
	(0.164)	(0.127)
(c) k = 5		
Full Sample	-0.187***	-0.168***
	(0.049)	(0.039)
Rural	-0.179***	-0.167***
	(0.054)	(0.043)
Urban	-0.361**	-0.289***
	(0.146)	(0.099)

Notes: Standard errors in brackets. Standard errors are calculated from bootstrapping with 250 replications. The propensity scores were calculated using the comprehensive set of variables (as in the third panel for each health outcome in Table 2). Results from Kernel matching method with bandwidth = 0.08.

*** $p < 0.01$.

** $p < 0.05$.

* $p < 0.1$.

Table 4. Inverse propensity score weighted estimates of the effect food insecurity on health outcomes

	WAZ	HAZ
Full Sample	-0.192***	-0.174***
	(0.036)	(0.034)
Rural	-0.152***	-0.139***
	(0.038)	(0.028)
Urban	-0.253**	-0.230***
	(0.111)	(0.082)

Notes: Standard errors in brackets. Standard errors are calculated from bootstrapping with 250 replications. The propensity scores were calculated using the comprehensive set of variables (as in the third panel for each health outcome in Table 2).

*** $p < 0.01$.

** $p < 0.05$.

* $p < 0.1$.

Table 5. Robustness to omitted variables: Oster Bounds

	R_{max} = 1.1R		R_{max} = 1.3R		R_{max} = 1.5R	
	WAZ	HAZ	WAZ	HAZ	WAZ	HAZ
Full Sample						
δ = 0.25	[-0.096, -0.090]	[-0.070, -0.066]	[-0.096, -0.078]	[-0.070, -0.056]	[-0.096, -0.066]	[-0.070, -0.046]
δ = 0.50	[-0.096, -0.084]	[-0.070, -0.061]	[-0.096, -0.059]	[-0.070, -0.042]	[-0.096, -0.034]	[-0.070, -0.022]
δ = 0.75	[-0.096, -0.078]	[-0.070, -0.056]	[-0.096, -0.040]	[-0.070, -0.027]	[-0.096, -0.002]	[-0.070, 0.003]
δ = 1.00	[-0.096, -0.072]	[-0.070, -0.051]	[-0.096, -0.021]	[-0.070, -0.012]	[-0.096, 0.032]	[-0.070, 0.030]
Rural						
δ = 0.25	[-0.070, -0.067]	[-0.054, -0.051]	[-0.070, -0.059]	[-0.054, -0.045]	[-0.070, -0.051]	[-0.054, -0.040]
δ = 0.50	[-0.070, -0.062]	[-0.054, -0.048]	[-0.070, -0.047]	[-0.054, -0.037]	[-0.070, -0.031]	[-0.054, -0.025]
δ = 0.75	[-0.070, -0.059]	[-0.054, -0.045]	[-0.070, -0.035]	[-0.054, -0.028]	[-0.070, -0.010]	[-0.054, -0.010]
δ = 1.00	[-0.070, -0.055]	[-0.054, -0.042]	[-0.070, -0.022]	[-0.054, -0.019]	[-0.070, 0.012]	[-0.054, 0.006]
Urban						
δ = 0.25	[-0.134, -0.130]	[-0.135, -0.132]	[-0.134, -0.122]	[-0.135, -0.125]	[-0.134, -0.114]	[-0.135, -0.117]
δ = 0.50	[-0.134, -0.126]	[-0.135, -0.128]	[-0.134, -0.110]	[-0.135, -0.113]	[-0.134, -0.093]	[-0.135, -0.098]
δ = 0.75	[-0.134, -0.122]	[-0.135, -0.125]	[-0.134, -0.098]	[-0.135, -0.102]	[-0.134, -0.072]	[-0.135, -0.078]
δ = 1.00	[-0.134, -0.118]	[-0.135, -0.121]	[-0.134, -0.085]	[-0.135, -0.090]	[-0.134, -0.050]	[-0.135, -0.058]

Notes: δ shows how strongly the unobservables drive treatment assignment relative to the observables. R_{max} is the maximum R-squared under the "full" model. R is the R-squared under the estimated model with comprehensive controls.

Table 6. Heterogeneity Analysis

	WAZ	HAZ
I. Cohort		
Younger Cohort (N = 7,132)	-0.099***	-0.077***
	(0.033)	(0.027)
Older Cohort (N = 1,780)	-0.080	-0.065
	(0.076)	(0.059)
II. Caste		
SC/ST (N = 2,746)	-0.089*	-0.038
	(0.051)	(0.040)
OBC (N = 4,316)	-0.036	-0.049
	(0.042)	(0.035)
Others (N = 1,850)	-0.291***	-0.186***
	(0.085)	(0.069)
III. Religion		
Hindu (N = 8,174)	-0.089***	-0.068***
	(0.031)	(0.025)
Others (N = 738)	-0.048	-0.009
	(0.126)	(0.110)
IV. Wealth		
Below Median (N = 3,594)	-0.038	-0.039
	(0.040)	(0.032)
Equal to/Above Median (N = 5,318)	-0.146***	-0.103***
	(0.046)	(0.038)

Notes: Robust standard errors in brackets. Regressions control for all covariates used in the "Comprehensive controls" specification (Table 2). SC denotes Scheduled Caste, ST denotes Scheduled Tribe and OBC denotes Other Backward Class.

*** $p < 0.01$.

** $p < 0.05$.

* $p < 0.1$.

Figure 1. Average WAZ and HAZ over time by food insecurity status

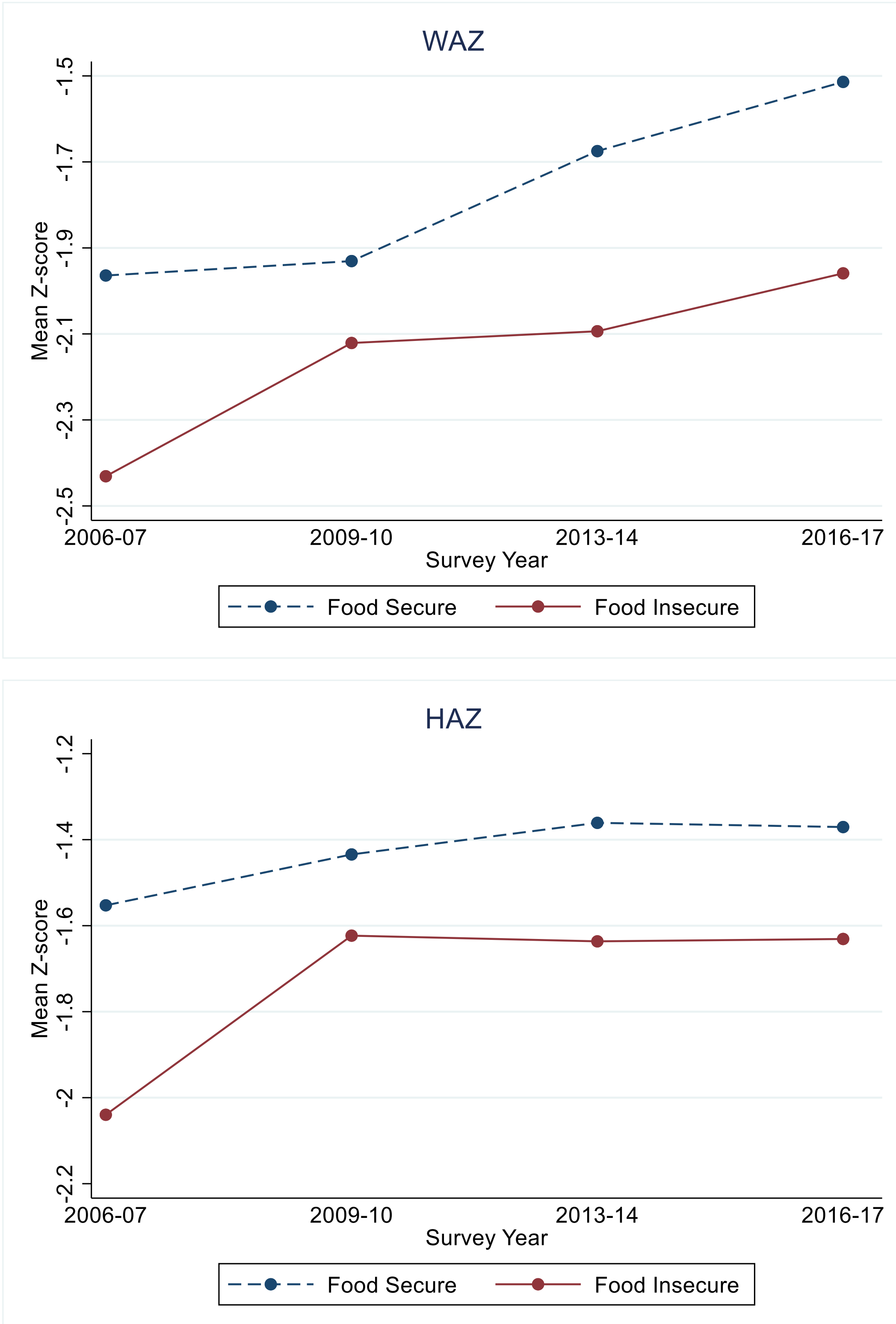


Figure 2. Conditional Quantile Treatment Effect

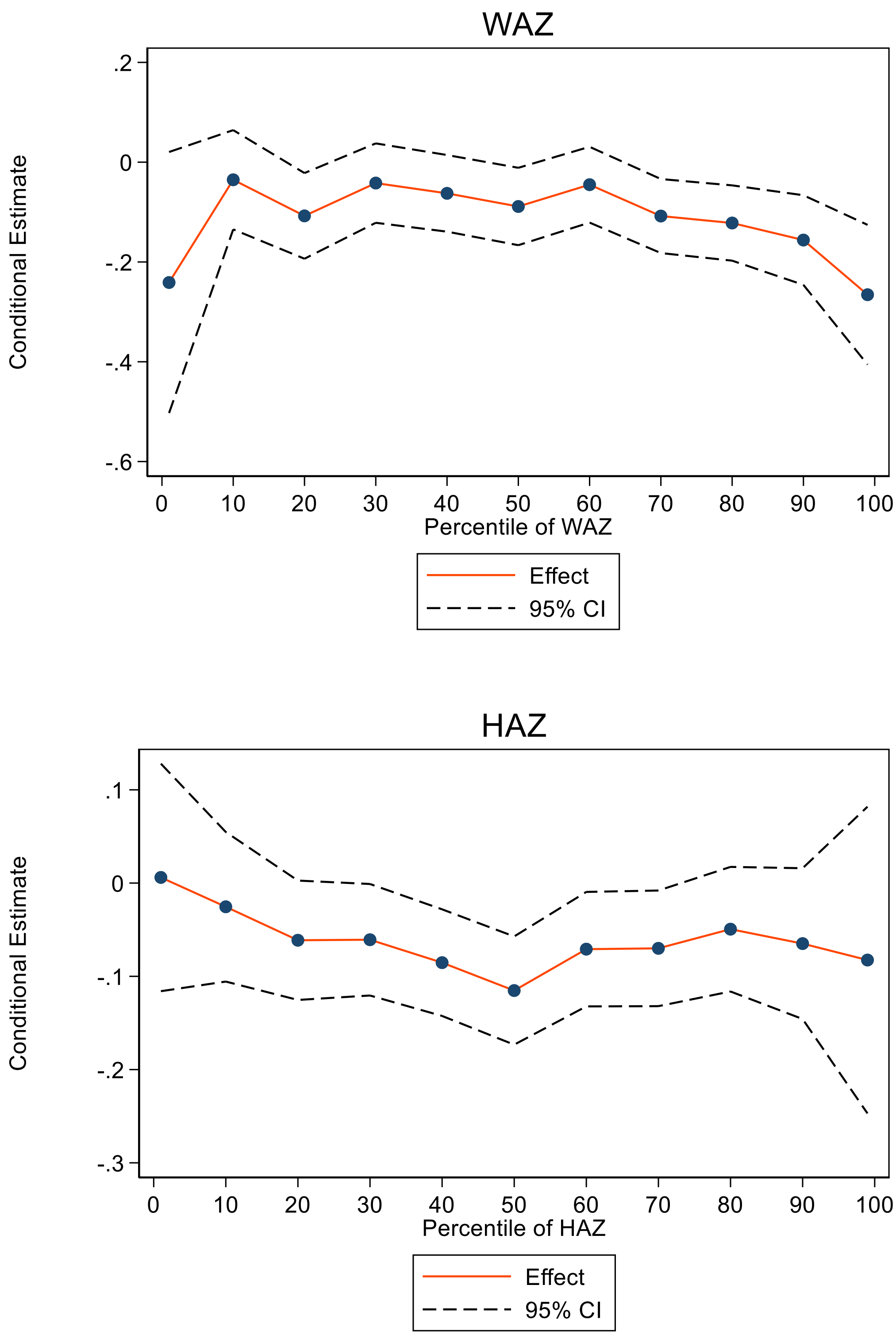


Figure 3. Conditional Quantile Treatment Effect, Rural versus Urban

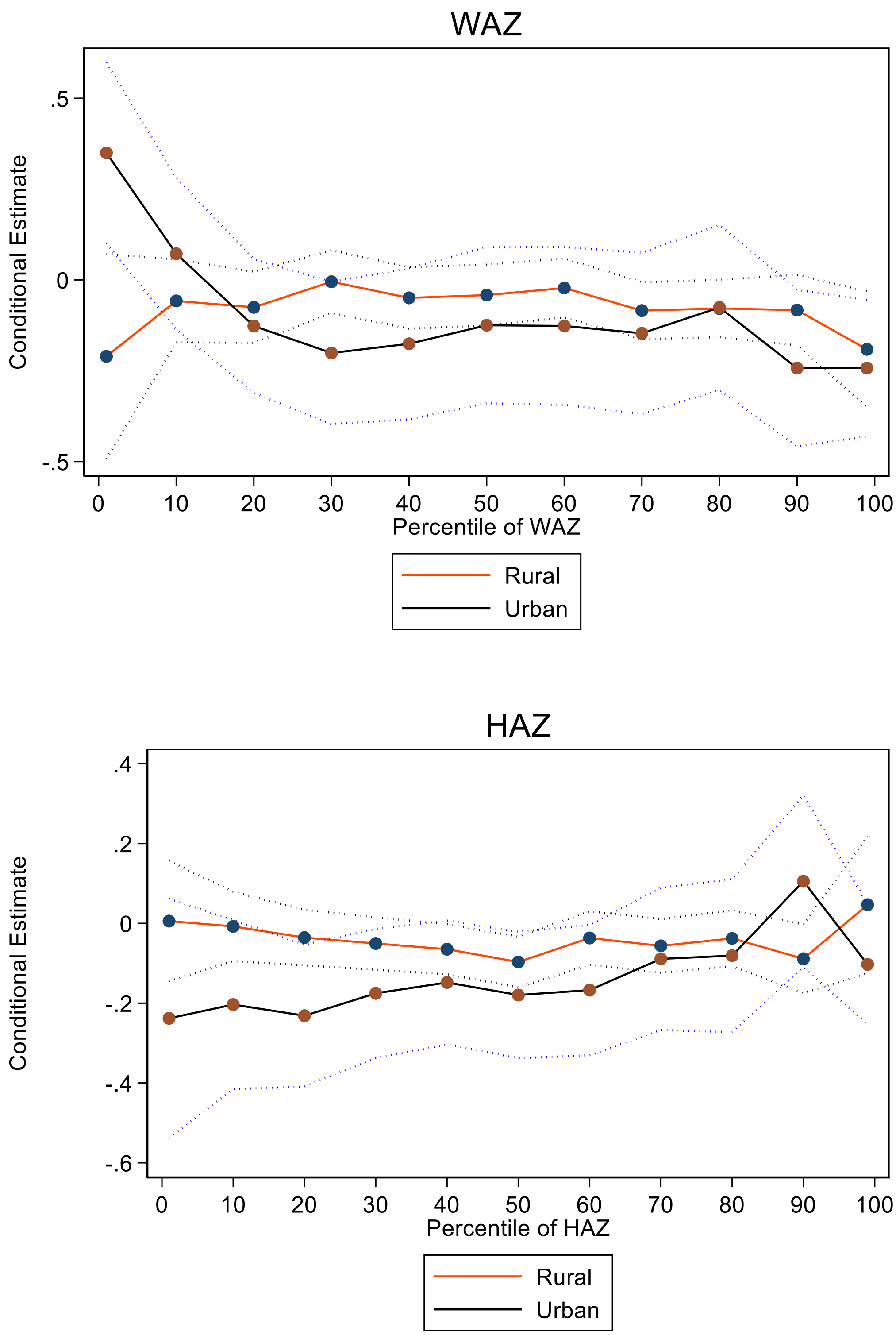
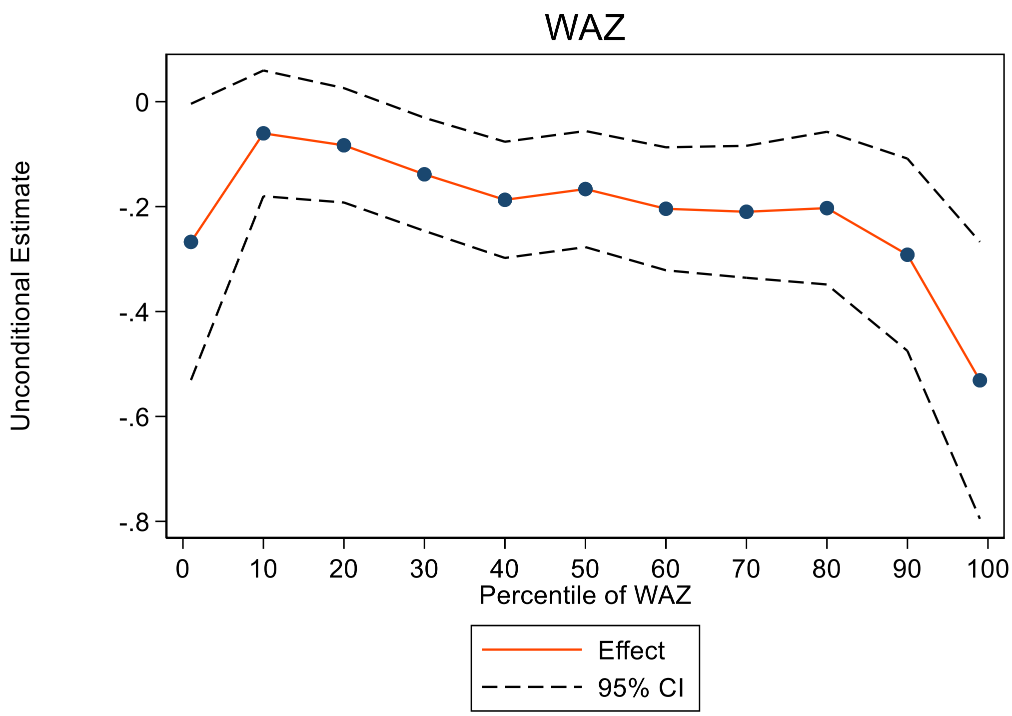


Figure 4. Unconditional Quantile Treatment Effect



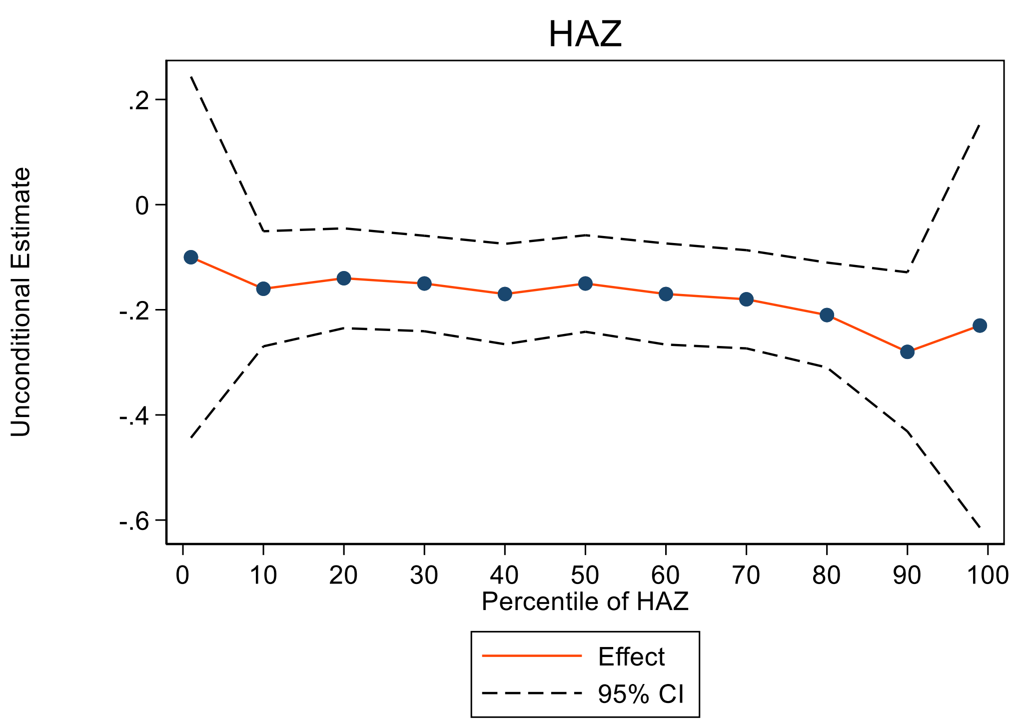
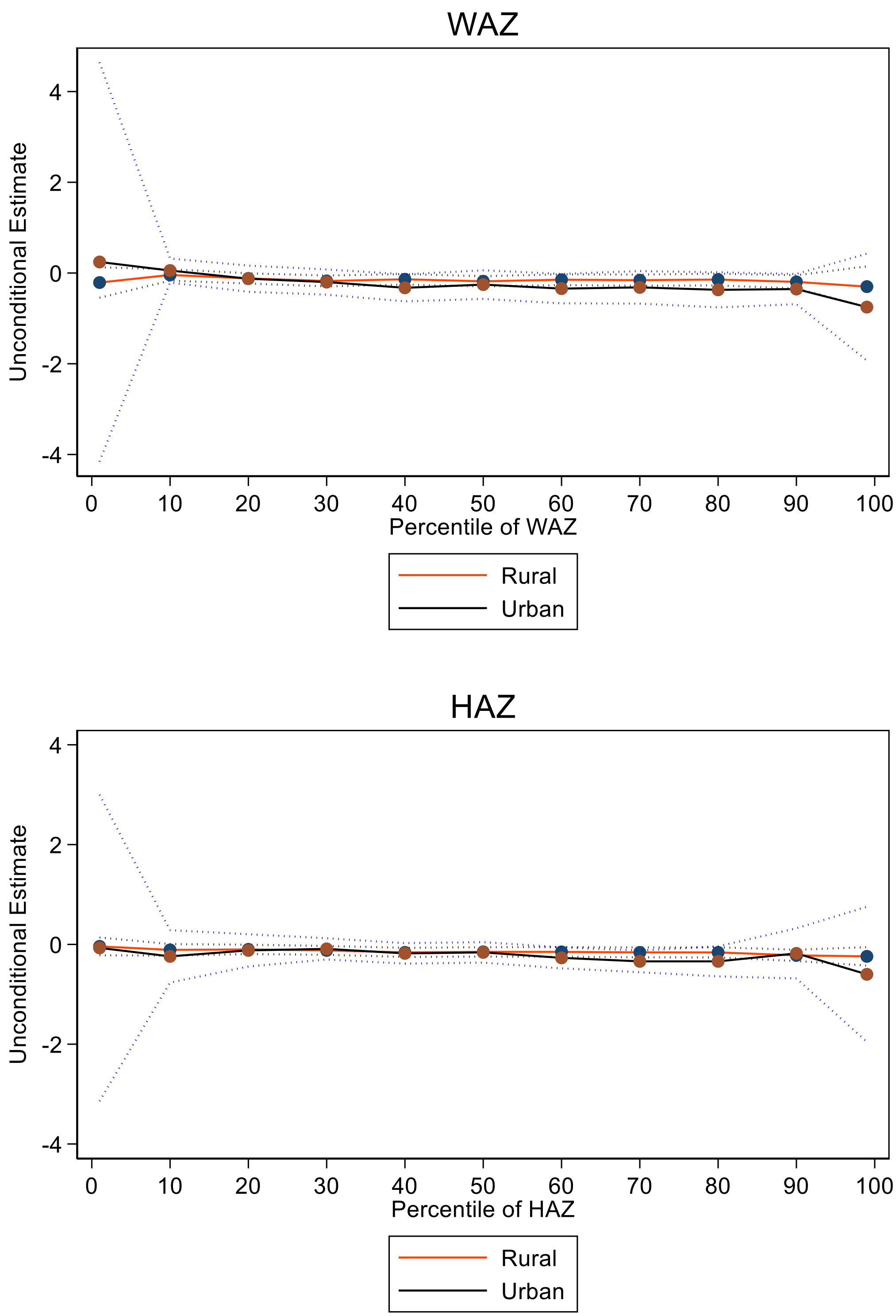


Figure 5. Unconditional Quantile Treatment Effect, Rural versus Urban



Appendix

Table A1. Household Food Insecurity Access Scale (HFIAS): Underlying Questions

(i)	In the past 12 months, did you ever worry that your household would run out of food before you get money to buy or could acquire more?
(ii)	Were you or any household member not able to eat the kinds of foods you want because of lack of money (e.g., no meat, no fish, no fruit, no sweet)?
(iii)	Did you or any household member have to eat a limited variety of foods due to lack of money (e.g., only rice and one vegetable, no meat)?
(iv)	Did you or any household member have to eat some foods that you did not want to eat because of a lack of money to obtain other types of food (e.g., wild foods, immature crops, broken rice, discarded food)?
(v)	Did you or any household member have to eat less (portion size) in a meal than you wanted because there was not enough food?
(vi)	Did you or any household member have to reduce the number of meals eaten a day because there was not enough food (e.g., skip breakfast or lunch)?
(vii)	Was there ever no food to eat in your household because of lack of money to get food?
(viii)	Did you or any household member go to sleep at night hungry because there was not enough food?
(ix)	Did you or any household member go a whole day and night without eating anything because there was not enough food?

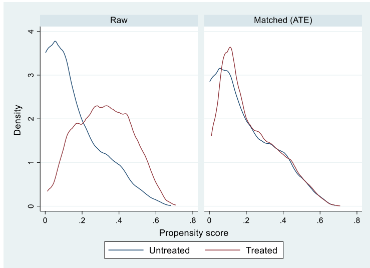
Table A2. Propensity score estimates of the effect food insecurity on health outcomes, Matching statistics

	Matched			Controls		
I. Kernel						
Full Sample						
Treated	Yes = 1889	No = 0	Total = 1889	Used = 7023	Unused = 0	Total = 7023
Untreated	Yes = 7023	No = 0	Total = 7023	Used = 1889	Unused = 0	Total = 1889
Combined	Yes = 8912	No = 0	Total = 8912	Used = 8912	Unused = 0	Total = 8912
Rural						
Treated	Yes = 1596	No = 0	Total = 1596	Used = 5011	Unused = 5	Total = 5016
Untreated	Yes = 5011	No = 5	Total = 5016	Used = 1596	Unused = 0	Total = 1596
Combined	Yes = 6607	No = 5	Total = 6612	Used = 6607	Unused = 5	Total = 6612
Urban						
Treated	Yes = 293	No = 0	Total = 293	Used = 2007	Unused = 0	Total = 2007
Untreated	Yes = 2007	No = 0	Total = 2007	Used = 293	Unused = 0	Total = 293
Combined	Yes = 2300	No = 0	Total = 2300	Used = 2300	Unused = 0	Total = 2300
II. k-Nearest Neighbor						
(a) k = 1						
Full Sample						
Treated	Yes = 1889	No = 0	Total = 1889	Used = 1382	Unused = 5641	Total = 7023
Untreated	Yes = 7023	No = 0	Total = 7023	Used = 1449	Unused = 440	Total = 1889
Combined	Yes = 8912	No = 0	Total = 8912	Used = 2831	Unused = 6081	Total = 8912
Rural						
Treated	Yes = 1596	No = 0	Total = 1596	Used = 1146	Unused = 3870	Total = 5016
Untreated	Yes = 5011	No = 5	Total = 5016	Used = 1178	Unused = 418	Total = 1596
Combined	Yes = 6607	No = 5	Total = 6612	Used = 2324	Unused = 4288	Total = 6612
Urban						
Treated	Yes = 293	No = 0	Total = 293	Used = 228	Unused = 1779	Total = 2007
Untreated	Yes = 2007	No = 0	Total = 2007	Used = 245	Unused = 48	Total = 293
Combined	Yes = 2300	No = 0	Total = 2300	Used = 473	Unused = 1827	Total = 2300
(b) k = 3						
Full Sample						
Treated	Yes = 1889	No = 0	Total = 1889	Used = 2965	Unused = 4058	Total = 7023
Untreated	Yes = 7023	No = 0	Total = 7023	Used = 1836	Unused = 53	Total = 1889
Combined	Yes = 8912	No = 0	Total = 8912	Used = 4801	Unused = 4111	Total = 8912
Rural						
Treated	Yes = 1596	No = 0	Total = 1596	Used = 2418	Unused = 2598	Total = 5016
Untreated	Yes = 5011	No = 5	Total = 5016	Used = 1549	Unused = 47	Total = 1596
Combined	Yes = 6607	No = 5	Total = 6612	Used = 3967	Unused = 2645	Total = 6612

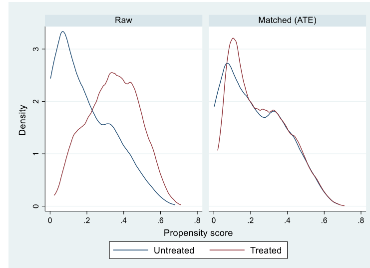
Urban						
Treated	Yes = 293	No = 0	Total = 293	Used = 551	Unused = 1456	Total = 2007
Untreated	Yes = 2007	No = 0	Total = 2007	Used = 288	Unused = 5	Total = 293
Combined	Yes = 2300	No = 0	Total = 2300	Used = 839	Unused = 1461	Total = 2300
(c) k = 5						
Full Sample						
Treated	Yes = 1889	No = 0	Total = 1889	Used = 3795	Unused = 3228	Total = 7023
Untreated	Yes = 7023	No = 0	Total = 7023	Used = 1875	Unused = 14	Total = 1889
Combined	Yes = 8912	No = 0	Total = 8912	Used = 5670	Unused = 3242	Total = 8912
Rural						
Treated	Yes = 1596	No = 0	Total = 1596	Used = 3019	Unused = 1997	Total = 5016
Untreated	Yes = 5011	No = 5	Total = 5016	Used = 1585	Unused = 11	Total = 1596
Combined	Yes = 6607	No = 5	Total = 6612	Used = 4604	Unused = 2008	Total = 6612
Urban						
Treated	Yes = 293	No = 0	Total = 293	Used = 777	Unused = 1230	Total = 2007
Untreated	Yes = 2007	No = 0	Total = 2007	Used = 293	Unused = 0	Total = 293
Combined	Yes = 2300	No = 0	Total = 2300	Used = 1070	Unused = 1230	Total = 2300

Figure A1. Distribution of propensity scores, pre- and post-matching

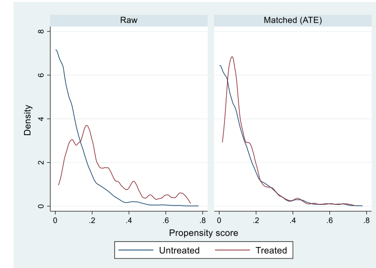
Kernel



Full Sample

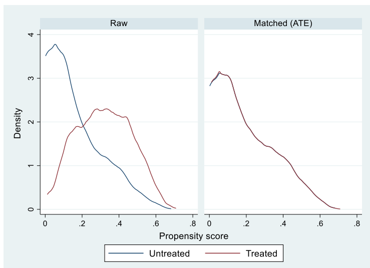


Rural



Urban

k-Nearest Neighbor (k=1)



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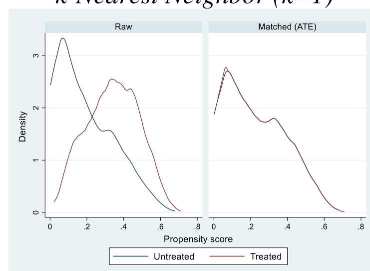

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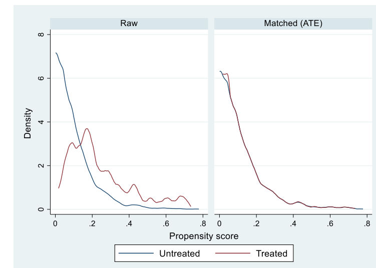
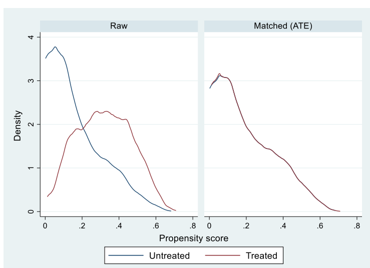
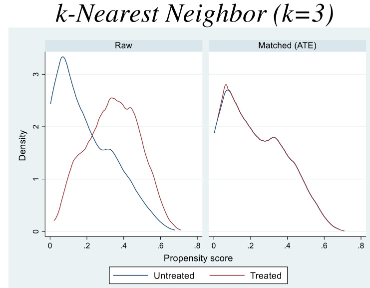


Urban

k-Nearest Neighbor (k=3)



Full Sample



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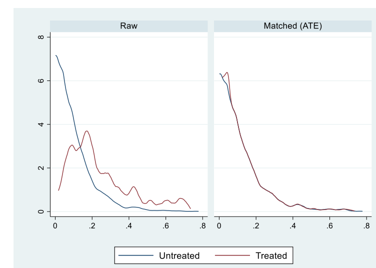
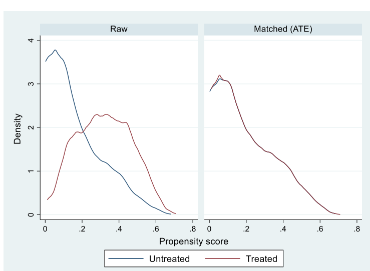
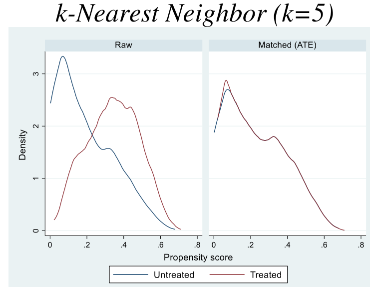


Urban

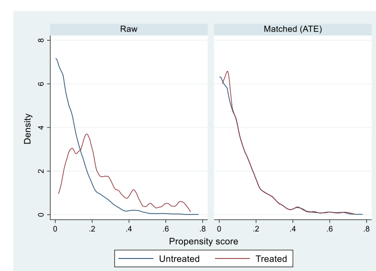
k-Nearest Neighbor (k=5)



Full Sample



Rural



Urban