Seasonal variation in nutritional status is a concern in sub-Saharan Africa. Seasonality in the food consumption of young Tanzanian children has a substantial and negative impact on later life outcomes. Seasonal variation in adult nutritional status has implications for labor productivity and prenatal health. Just as mean poverty status or mean health status varies within households, seasonal patterns in health status are likely to vary within households, as well as the mechanisms underlying seasonal variation. We parameterize and compare seasonality in nutritional status across multiple types of household members in rural, farming households in Tanzania, using a novel anthropometric measure of body mass index z-score that is comparable across adults and children. Young children not yet in school and working adults are most vulnerable to seasonal fluctuations in nutritional status. Children in school and older adults are relatively shielded. Seasonal variation in the nutritional status of working adults can be partly explained by variation in dietary quality and agricultural labor hours. Seasonal variation in the nutritional status of young children is not explained by either factor, nor is it mitigated by market access. Our results suggest we do not understand the data generating process behind seasonality in the nutritional status of young children, despite the critical implications of this seasonality for development and later life productivity.

Keywords: Intra-household | seasonality | BMI Z-score | nutrition

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1 Introduction

Seasonal variation in nutritional status is a major concern in sub-Saharan Africa. Both children’s and adult’s anthropometric outcomes vary predictably across the agricultural season (Abay and Hirvonen, 2017; Maleta et al., 2003; Dercon and Krishnan, 2000a). In children this variation has serious, negative implications for later life health and human capital accumulation (Christian and Dillon, 2018; Lokshin and Radyakin, 2009). In adults it has implications for agricultural labor productivity, and perhaps cognitive capacity (Haddad and Bouis, 1991; Croppenstedt and Muller, 2000; Mani et al., 2013).

Seasonal variability in anthropometric outcomes is generally attributed to seasonal variation in food availability, food prices and income (Gilbert, Christiaensen and Kaminski, 2017; Kaminski, Christiaensen and Gilbert, 2016; Hirvonen, Taffesse and Hassen, 2016; Kaminski, Christiaensen and Gilbert, 2014; Dercon and Krishnan, 2000b). In fact, a number of papers document seasonal variability in calorie consumption, dietary diversity, food expenditure, and food sourcing behaviors in rural, sub-Saharan Africa (Ayenew et al., 2018; Abizari et al., 2017; Sibhatu and Qaim, 2017; Hirvonen, Taffesse and Hassen, 2016; Chirwa, Dorward and Vigneri, 2011). Other, non-food seasonal patterns may also affect nutritional status and health. For instance, seasonal liquidity constraints impact propensity to sell labor (Fink, Jack and Masiye, 2018; Bandiera et al., 2017), with potential effects on energy expenditure and health (Rao and Raju, 2017). Disease environment also varies by season — for instance, seasonal spikes in malaria drive increases in mortality in infants, women and children (Anya, 2004; Baird et al., 2002).

Just as mean poverty or health status varies within households (Brown, Ravallion and Van De Walle, 2017), seasonal variation of poverty or health status is also likely to vary within households — by age, sex, job type, schooling status, social position within the household, or any number of other context-specific factors. Much supporting evidence exists for this hypothesis. A number of studies have found consumption to be less price-elastic or income-elastic for females or for other, less favored demographic groups (Alderman and Gertler, 1997; Behrman, 1988; Behrman and Deolalikar, 1990). Villa, Barrett and Just (2011) find the opposite amongst pastoralist households in East Africa; household heads bear the nutritional burden when income is low, while other cohorts enjoy nutritional gains when income is high. Using body mass index (BMI) to gauge nutritional status, Dercon and Krishnan (2000a) find risk sharing between men and women in agricultural households in Ethiopia, except in land-poor, southern households where women bare the brunt of their own illness shocks.1 Fafchamps and Quisumbing (1999) find that the gender division of labor tasks and leisure varied by season in rural Pakistan, with potential implications for calorie expenditure and health.

Despite all this suggestive evidence, no direct examination exists of family member specific, seasonal trends in health and welfare. Most datasets do not contain enough temporal variation within a given spatial area to examine any type of seasonal trend in welfare; those that do rarely contain individual-level health indicators. More critically, the comparison of seasonal trends across family member categories also necessitates a comparable metric for health, relevant for all family members. While child health status

1An alternate interpretation of this result is that BMI is more affected by illness for women than for men, for physiological reasons.
is often gauged through height-for-age or weight-for-height z-scores, adult health is often gauged through BMI. These two measures are not comparable.

Our first contribution is to parameterize and to compare seasonality in nutritional status across multiple types of household members in rural, farming households, using a novel anthropometric measure of BMI Z-score that is comparable across adults and children (Naschold, 2018). We model seasonality in BMI Z-scores with a flexible, four term Fourier series. We then compare seasonal vulnerability across groups as measured by the amplitude – not level – of seasonal fluctuation in BMI Z-score. We find that young children not yet in school and working adults are most vulnerable to seasonal changes in nutritional status. Children in school experience only half of the seasonal differential that younger children and working-age adults experience. Older adults experience less seasonal variation than younger, working-age adults.

Second, we present evidence regarding the mechanism behind seasonal patterns, for each type of individual. We examine two simple mechanisms: dietary quality as proxied by household dietary diversity score, which is known to fluctuate seasonally, and agricultural labor expenditure, which also varies by agricultural season. We also briefly examine non-agricultural labor; it does not exhibit a seasonal pattern, and does not help to explain seasonal variation in BMI Z-scores. Not surprisingly, seasonality in the nutritional status of children in school is associated (fairly weakly) with dietary quality, but not associated with agricultural labor. For working age women and men, accounting for either dietary diversity or agricultural labor mitigates residual seasonality in nutritional status, and accounting for both together mitigates residual seasonality by 50 and 20 percent, respectively. This suggests that working adults are not being compensated fully with improved dietary intake for their increased calorie expenditure during the demanding agricultural season. Perhaps most importantly, we find that neither mechanism helps to explain seasonality in the nutritional status of young children not yet in school.

We might expect market integration to mitigate seasonality in nutritional status, by weakening the linkage between production and consumption and improving access to diverse, healthy food during lean season. Proximity to markets might also provide employment opportunities during lean season or improve the constancy of nutritional status in some other way. However, we find that proximity to markets in rural Tanzania fails to mitigate the seasonality of BMI Z-scores. For children and working male adults, in fact, seasonality in nutritional status is actually higher for those closer to market.

In Section 2 we provide information on the agricultural cycle in Tanzania, and an overview of our data. In Section 3 we lay out our estimation strategy. In Section 4 we provide and discuss our results. In Section 5 we conclude.

2 Setting and Data

We use data from Tanzania’s National Panel Surveys, from 2008/9, 2010/11, 2012/13, and 2014/15. Households can be linked across the first three panel waves; the fourth wave is a new sample of households, but with a comparable spatial distribution and identical survey modules. Households are sampled within clusters, generally defined by
a village, and we have the geospatial location of each cluster. This dataset therefore critically allows us to view households in roughly the same geographic location over four waves, with variation over the agricultural season both across and within survey waves. We drop households who do not own farmland. Seasonal patterns in food intake, labor demands and nutritional status may vary across farming and non-farming families; our focus in this paper is on the former.

2.1 The Agricultural Cycle

Tanzania’s agricultural cycle revolves primarily around the long *Masika* rains, though some areas also experience a shorter rainy period called *Vuli*. Figure 1 displays an agricultural timeline ordering *Masika* rains and the planting/growing months, the *Masika* harvest, and the lean season, similar to that shown by the Food and Agricultural Organization (FAO) or the Famine Early Warning Systems Network (FEWS NET).\(^2\)\(^3\) It is general wisdom that *Masika* harvest begins in July and continues through August, and that lean season begins around October and ends around January, cut short by increased food availability accompanying the *Vuli* harvest. Twenty-five percent of households in our dataset report a *Vuli* harvest; they are geographically concentrated in the north of the country and along the coast.

However, we have left the months unlabeled in Figure 1, because the precise timing of the *Masika* rains and the *Masika* harvest actually shifts over space. Figure 2 maps rainfall totals, in millimeters, by month in Tanzania. This figure was made using 0.25 degree resolution precipitation data from the European Center for Medium-Range Weather Forecasting (ECMRWF). Rainfall begins earliest in the north-east of the country and comes latest to the center of the country. Figure 3 maps the cluster-average month of households beginning the *Masika* harvest. (All households list this month in each wave of the survey, and we average that month over households and survey rounds within each cluster.) In line with the rainfall patterns shown in Figure 2, harvest occurs first in the north-east of the country, and last in the center of the country. This will necessarily shift the calendar month of lean season across the country, or the calendar month of any event aligning with the agricultural cycle. That is, while households may experience similar seasonal trends in food availability, welfare and health, the calendar timing of these trends will vary across space.

For this reason, we model seasonality not according to calendar month, but according to “months since the *Masika* harvest.” The month of *Masika* harvest is determined uniquely for every cluster as in Figure 3: the average month that households within the cluster report beginning their own *Masika* harvest, across all four waves of data. This date does not change over time or over households within a cluster. However, “months since the *Masika* harvest” is obtained as the difference between the household-specific survey interview date and the cluster-specific *Masika* harvest date, and therefore changes over households and rounds, since each household is interviewed at a different time in each round.\(^4\)

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\(^3\)http://www.fao.org/giews/countrybrief/country.jsp?code=TZA

\(^4\)We do not include *Vuli* rains in this graphic as the timing of *Vuli* rains is unclear. It varies by location and changes by year, according to farmer reports in our data.

\(^4\)Most households in a cluster are interviewed within a similar time frame for any given round, but this
For analysis of seasonal trends in household characteristics or individual behaviors, we would ideally wish for the distribution of survey dates to be geographically random in every wave, making “months since the Masika harvest” geographically random. In reality, this distribution is close to but not precisely random. Figures A1-A4 map the median month of survey for each enumeration area, for survey waves 1-4. These maps do not show a spatial patterning in color (i.e., in survey time), suggesting random geographic patterning in the temporal roll-out of enumeration teams. However, we check this patterning parametrically by regressing interview month on latitude and longitude, both with and without region effects. Latitude and longitude do significantly predict interview month in unconditional regressions (Tables A1), but their influence falls sharply and becomes insignificant once regional fixed effects are in place (Table A2). They also explain a negligible portion of within-region R-squared — only 0.3 percent of within-region variation when all rounds are pooled. Given these results, we include region fixed effects in all parametric analyses, as well as latitude and longitude to be conservative. We proceed with the assumption that spatial variation in survey timing is as good as conditionally random.

2.2 Nutritional Status

We view age, weight, and height for almost all household members. This allows us to estimate BMI Z-scores for each individual, constructed according to the methodology laid out by Naschold (2018). This method is based on the statistical method used for the WHO 2006 Growth Standards and the WHO 2007 Growth Reference (WHO, 2006; Onis et al., 2007), but extends to construct BMI z-scores for all adults over 20 years old. Essentially, we calculate BMI z-scores for household members of all ages according to age-specific, sex-specific anthropometric reference data for children and adults.5 Our reference population are the first three rounds of the National Health and Nutrition Examination Survey (NHANES), from 1975, 1980, and 1998. These data pre-date the steep increase in obesity in the US and represent a healthy reference population, and have historically been used to construct anthropometric growth curves such as the 2000 Center for Disease Control (CDC) and the 1977 National Center for Health Statistics (NCHS) growth curves. The latter was adopted by the World Health Organization for world-wide use.

To examine aggregate or sub-group trends in welfare over seasons, we would ideally wish for the demographic composition of the household to be stable over the course of a year. However, household gender ratios and the average age of household members changes over the year. In particular, working adult men are most scarce right around the time of harvest, and their numbers are highest around 5 months after harvest (Figure A5).6 This means that household-average age is also highest around 5 months after harvest (Figure A6). This fluctuation in gender ratios will obscure aggregate

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5 We define age in months until 20 years of age, after which it is defined in years. The exception is round 4, where we view age in years only for individuals above 60 months. We include these individuals in our sample, calculating their BMI z-scores using age in years. Dropping this group completely has no appreciable effect on our results, besides slightly increasing the seasonal variability in nutritional status of young children not yet in school.

6 This trend may be due to seasonal migration; we are not aware of it being previously documented.
seasonal trends in BMI Z-scores if male BMI Z-scores are systematically different from female BMI Z-scores. And in fact, Tanzanian BMI Z-scores do vary systematically by gender after the point of puberty (Figure A7). They also differ systematically by age. At 12.5 BMI Z-scores begin rising for girls. At 15 BMI Z-scores begin a similar rise for boys, but they never "catch up" to teenage girls, and BMI Z-scores remain higher for adult women than for adult men. The differential remains stable until around the age of 50 when it begins converging; BMI Z-scores meet again around age 70.

There are two possible reasons for the gender differential and age trend in BMI Z-scores. First, the average Tanzanian woman may truly enjoy better nutritional status than the average Tanzania man in our sample, with that difference growing less as men and women age. Second, these gender-specific trends over age may stem from physiological difference between the populations in Tanzania and the NHANES reference population. While examining this differential is important, it has been done elsewhere and outside the scope of this paper (Jackson et al., 2009; Heymsfield et al., 2016). Here we examine seasonal variation in Z-scores, rather than levels. We therefore wish to correct for this differential, not explain it. To do so, we control for age-gender fixed effects in all parametric analysis, thereby partialling out any variation in BMI Z-scores over time that might be due to changing demographic composition within the household. Also, we do examine men and women separately for working adults, where the BMI Z-score differential is greatest.

Introducing age-gender fixed effects in our parametric analysis has important implications for the interpretation of our results. We are essentially anchoring BMI Z-score at zero for every age-sex bracket. We cannot, therefore, compare the "average" nutritional status of various family member categories, as manifest by their average BMI Z-scores. It is not meaningful to compare BMI Z-scores across individuals of different ages or genders, given that the NHANES reference population may be more or less comparable for Tanzanian individuals of certain ages and genders. Instead, we compare only the magnitude of seasonal variation in BMI Z-scores across family member categories. In other words, we restrict our attention to seasonal variation in nutritional status, and ignore average nutritional status. This seasonal aspect of nutritional vulnerability is important. Christian and Dillon (2018) find that the negative relationship between seasonality in childhood consumption and subsequent human capital is 30-60 percent the magnitude of the positive relationship between average childhood consumption and subsequent human capital, in Tanzania.

### 2.3 Other Characteristics

Dietary diversity is widely used as an indicator of dietary quality, and is correlated with nutrient adequacy, energy intake and household food security (Ogle, Hung and Tuyet, 2001; Hoddinott and Yohannes, 2002; Torheim et al., 2004; Steyn et al., 2006; Kennedy et al., 2007; Moursi et al., 2008). We construct one of the most widely used household-level dietary diversity measures: the 12-scale household dietary diversity score developed by the Food and Nutrition Technical Assistance (FANTA) Project of the United States Agency of International Development (Swindale and Bilinsky, 2006). We construct this score using data on household food consumption over the last 7 days, as do Jones, Shrinivas and Bezner-Kerr (2014) and Sibhatu, Krishna and Qaim (2015). The survey’s food consumption module includes a long and fairly comprehensive list of nutritional food items.
common foods in Tanzania.7 Household dietary diversity score is a count (0-12) of food groups consumed from the following list: cereals, roots and tubers, vegetables, fruits, meat other than seafood, eggs, fish and seafood, pulses/legumes/nuts, milk products, oils/fats, sugar/honey, miscellaneous other food.

We view agricultural labor hours expended on farm for all individuals within the last 7 days, as well as labor hours spent on non-agricultural household business or spent for an external job/apprenticeship. We aggregate all non-agricultural labor together into one variable, in part because the nuances of the survey questions change over the four survey rounds, making this aggregate the most comparable quantity across rounds. The survey question on agricultural labor hours is identical across rounds.

For some households we view recent expenditure on maize flour, an important staple in Tanzania, within the last 7 days. From this expenditure, and the quantity purchased, we may calculate unit values for maize flour. Ideally, we might examine seasonal trends in these unit values, which are surely relevant for food consumption and health. However, this information is missing for many households, and even for entire enumeration areas. Figure A8 maps (log) median unit values for maize flour in each enumeration area, for each round. Red crosses mark the enumeration areas with no data on maize flour, because no households in the EA purchased maize flour during the 7-day window of interest in that round. This is most common in the center of the country. Interpolating missing values in this variable would surely create spatially correlated measurement error, and so we do not include unit values for maize flour in our core analysis.8 The price of maize flour is in any case interesting as a predictor of food availability, and hence a proxy for dietary quality.9 Household dietary diversity serves as a more direct measure of dietary quality, and so we use this variable instead of the price of maize flour.

Geospatial coordinates for all enumeration areas allow us to estimate distance to the nearest regional market for each household. We use the 18 regional markets examined by Baffes, Kshirsagar and Mitchell (2017): Bukoba, Musoma, Mwanza, Arusha, Moshi, Shinyanga, Tabora, Singida, Tanga, Dodoma, Morogoro, Dar es Salaam, Iringa, Sumbawanga, Mbeya, Lindi, Mtwara, and Songea. Additionally we drop farming households that are within ten kilometers of Dar Es Salaam’s center, because while these households technically own farms and report agricultural production, they are unlikely to actually live on those farms.

We examine seasonality of BMI Z-scores across five types of family members: children under the age of 8 who are not in school; children, teens, and young adults who are enrolled in school and under the age of 22; teen or adult women who are not in school, aged 12-55; teen or adult men who are not in school, aged 12-55; and adults older than 55. We chose these five categories to represent the nutritionally vulnerable groups of...

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7This list includes many varieties and many forms of cereals, tubers and starches, multiple forms of bread/pasta, and multiple types of sugars and sweets, nuts and seeds, vegetables, fruits, meats and fish, eggs and milk sources, oils and fats, spices, caffeinated and alcoholic drinks, and other types of drinks. It includes only one aggregate listing for pulses: “peas, beans, lentils, and other pulses.”

8Alternate data sources exist for the price of maize flour in Tanzania, but none as spatially disaggregated as we would need for our analysis.

9The price of maize flour might also predict agricultural income. However, because most families sell crops directly after harvest, this income effect is unlikely to exist across seasons or vary seasonally.
young children and older adults, to test the oft-posed hypothesis that women are more nutritionally vulnerable than men, and to capture the fact that students are likely to consume food and expend energy differently than non-students.\textsuperscript{10} The choice was also made, to some extent, inductively: these groups have evident differences in the seasonal trends of their BMI Z-scores. In fact, no significant difference exists across the seasonal trends of male and females in any category, except for that of teens and adults aged 12-55 who are not in school.

Table 1 summarizes our key variables for each of these five groups. BMI Z-scores are lowest, on average, for adults males and older adults, and highest for pre-school children, followed by female adults. Though again, any difference in levels is difficult to interpret, and not the focus of our analysis. Household dietary diversity varies little across family member categories, though the older adults live in households with the lowest dietary diversity. Agricultural and non-agricultural labor hours are listed at the extensive and (non-transformed) intensive margin in Table 1, though they are specified by an inverse hyperbolic sine transform in regressions. Only 26\textsuperscript{[19]} percent of children in school engaged in agriculture [non-agricultural labor] during the week of interview, while 67\textsuperscript{[33]} percent of female adults did, and 70\textsuperscript{[37]} percent of male adults did. Children in school also provided fewer labor hours than adults, conditional on providing labor. Older adults were slightly less likely to engage in agriculture than working-age adults, but provided comparable levels of agricultural labor contingent on providing any. Young children live in households that are notably closer to regional markets than the norm, and older adults live in households that are notably further from regional markets than the norm.

3 Empirical Strategy

We begin by examining non-parametric seasonal trends in BMI Z-score status, dietary diversity, and agricultural labor at the household level. This household-aggregate examination of seasonality mimics much of the past literature. And in fact, like Ayenew et al. (2018), Sibhatu and Qaim (2017) and Hirvonen, Taffesse and Hassen (2016), we cannot parse dietary diversity by household members, because we have access only to a household-level food consumption module. Nutritional status and agricultural labor expenditure can be parsed, but it is helpful to first begin with aggregate trends.

Next we parameterize the seasonality of nutritional status (BMI Z-scores) as a sinusoidal function of time. Sinusoids are often used to capture seasonality in economic and biophysical phenomena because they require fewer parameters than a series of weekly or monthly fixed effects. Gilbert, Christiaensen and Kaminski (2017) estimate seasonality in African crop prices using a specification that allows some flexibility in the shape of the seasonal pattern but requires seasonal symmetry and allows only one peak and one trough per year. Barrett et al. (2003) estimate seasonality in livestock prices in northern Kenya using a more flexible specification. A number of related sinusoidal functions have been used to model the seasonal component of energy prices (Erlwein,
Benth and Mamon, 2010; Escribano, Ignacio Peña and Villaplana, 2011; Janczura et al., 2013). Parameterizing seasonality as a sinusoidal function is superior to parameterizing it via a series of month dummies for a few reasons. Gilbert, Christiaensen and Kamiński (2017) show that when samples are short or seasonality is poorly defined, this dummy variable method can over-estimate the amplitude of seasonality in prices. A series of dummy variables is far less parsimonious. Most importantly, dummy variables do not constrain predictions to meet between January and December, or more generally to be a continuous function of time – i.e., they does not enforce cyclicity.

We use a four-term Fourier series consisting of two annual and two 6-month cycles, as commonly seen in signal processing or physics (Bevis and Brown, 2014). Equation 1 models BMI Z-scores for each individual in family member category \( c \) living in region \( r \) and observed in survey year \( y \) as a sinusoidal function of time \( t \). Because we specify time as running from 0 to 1, it follows that \( \tau_1 = 1 \) and \( \tau_2 = 1/2 \). Including the second order terms that normalize by \( \tau_2 \) allows for non-symmetry and any combination of annual and 6-month cycles. Controls \( X_{cryn}^{c} \) contain regional fixed effects, survey year fixed effects, age-gender fixed effects, latitude and longitude, as necessary to cleanly identify seasonality.

\[
BMIZ_{cryn}^{c} = \alpha^{c}\sin\left(\frac{2\pi t}{\tau_1}\right) + \beta^{c}\cos\left(\frac{2\pi t}{\tau_1}\right) + \gamma^{c}\sin\left(\frac{2\pi t}{\tau_2}\right) + \delta^{c}\cos\left(\frac{2\pi t}{\tau_2}\right) + \pi^{c}X_{cryn}^{c} + \epsilon_{cryn}
\]

When parameterizing a Fourier series time \( t \) can be measured in any unit; it might run from 0 to 365 if measured in days, or from 0 to 12 if measured in months. Here we specify time not as interview month, but in months since the last Masika harvest, at the time of interview. This is because the timing of seasonal cycles shifts from east to west (Figure 3), as rainfall patterns and therefore crop patterns shift. Modeling seasonal patterns for all of Tanzania according to calendar date of interview would therefore induce spatially-correlated error in model specification. Defining time as relative to the month of harvest allows a slow spatial shift in the timing of seasonal cycles.

Equation 1 allows us to measure seasonal vulnerability in terms of amplitude, and to compare vulnerability across family member categories. It also allows us to investigate whether the timing of greatest nutritional vulnerability varies across categories. It does not, however, provide any evidence regarding the data generating process behind seasonal patterns. Therefore, in Equation 2 we attempt to capture the two hypothesized mechanisms behind seasonal variation in nutritional status: quality of dietary intake, and physical exertion. We proxy for the first mechanism through household dietary diversity score. The second mechanism is captured by agricultural labor hours spent. Both variables are included as controls within \( M_{cryn}^{c} \) in Equation 2.

\[
BMIZ_{cryn}^{c} = \hat{\alpha}^{c}\sin\left(\frac{2\pi t}{\tau_1}\right) + \hat{\beta}^{c}\cos\left(\frac{2\pi t}{\tau_1}\right) + \hat{\gamma}^{c}\sin\left(\frac{2\pi t}{\tau_2}\right) + \hat{\delta}^{c}\cos\left(\frac{2\pi t}{\tau_2}\right)
\]

\[11\] Gilbert, Christiaensen and Kamiński (2017) use only first order terms. The sinusoidal function used by Barrett et al. (2003) is equivalent to our formulation under the constraint \( \delta^{c}=0 \). Rather than include our second two terms, they include \( \sin\left(\frac{2\pi t}{\tau_1}\right) \cos\left(\frac{2\pi t}{\tau_1}\right) \) as a third term, where \( t \) runs from 0 to 1 as in our specification, and \( \tau_1 = 1 \). From the trigonometric identity \( 2\cos(\theta)\sin(\theta) = \sin(2\theta) \), we can show \( \delta^{c}\left[2\cos(2\pi t) \sin(2\pi t)\right] = \delta^{c}\left[\sin(2\pi t \ast 2)\right] = \delta^{c}\sin\left(\frac{2\pi t}{\tau_2}\right) = \delta^{c}\sin\left(\frac{2\pi t}{\tau_2}\right) \).
For each family member type, we gauge not only the association between dietary diversity or agricultural labor and BMI Z-score, but also the reduction in residual seasonality that accompanies this control. We do this by comparing the amplitude of the sinusoidal function under Equation 1 vs. Equation 2. In fact, we estimate Equation 2 with \(M_{c}^{\text{ryt}}\) containing only dietary diversity, containing only agricultural labor hours, or containing both variables. This comparison provides suggestive evidence for the relative importance of each mechanism to the seasonality of nutritional status experienced by different types of family members.

If dietary diversity contributes to the seasonality of nutritional status, we might expect market integration to mitigate this seasonality. We therefore end by examining how seasonality in BMI Z-scores varies with distance to the nearest regional market, for each type of family member. We do this by estimating Equation 3, where distance to the nearest market is given by \(D_{\text{ryt}}\) and measured in log kilometers. We control for \(D_{\text{ryt}}\) directly as well as interacting \(D_{\text{ryt}}\) with the sinusoidal terms. This interaction allows both the shape and amplitude of seasonal patterns to shift with distance to market.

\[
BMIZ_{c}^{\text{ryt}} = \bar{\alpha}_{c} \sin\left(\frac{2\pi t}{\tau_{1}}\right) + \bar{\beta}_{c} \cos\left(\frac{2\pi t}{\tau_{1}}\right) + \bar{\gamma}_{c} \sin\left(\frac{2\pi t}{\tau_{2}}\right) + \bar{\delta}_{c} \cos\left(\frac{2\pi t}{\tau_{2}}\right) + \bar{\pi}_{c} X_{\text{ryt}} + \bar{\omega}_{c}^{	ext{ryt}} \tag{3}
\]

4 Results and Discussion

Figure 4 illustrates seasonal trends in household dietary diversity, total agricultural hours expended by all family members, and household-average BMI Z-scores, using (Epanechnikov) kernel-weighted local polynomials to smooth mean values. These aggregate relationships are striking: labor expenditure is highest as dietary quality is lowest. Average nutritional status is lowest during that same time period. The point of lowest average nutritional status is slightly later than the period traditionally considered “lean season” in Tanzania. Lean season is generally said to begin around 3 months after the start of Masika harvest, and to last about three months. Figure 4 suggests that for most Tanzanians the point of lowest nutritional status is about 2 months after lean season, suggesting that there is a slight lag between increased food availability and recovery of body mass.

Figure 5 illustrates the seasonal patterns estimated by Equation 1 for each family member category \(c\), conditional on regional fixed effects, survey year fixed effects, age-gender fixed effects, latitude and longitude. Predicted BMI Z-scores / nutritional status, cleansed of all controls, is overlaid on local polynomial predictions for a better sense of the data itself.\(^{12}\) The general shape of the seasonal trend is fairly similar across all individuals: the period of greatest nutritional vulnerability, given by the value of

\(^{12}\)These local polynomials are in fact semi-parametric: a local polynomial regression of the residual that arises from regressing BMI Z-scores on all controls, but not on the sinusoidal terms. The local polynomials are therefore cleansed of potentially biasing features just as the parametric predictions are.
“Low” in the title of each sub-figure, is always around 8 months after harvest, as suggested by Figure 4. Nutritional status is highest directly before and after harvest, when food is plentiful. Because heterogeneity exists in harvest timing, across space and crops and varieties, food availability rises even before the majority of farmers are beginning harvest. Table 2 holds the sinusoid coefficients estimated by Equation 1; they are not particularly meaningful when viewed in this fashion, which is why we visualize the shapes created from these coefficients in Figure 5.

Severity in the seasonality of nutritional status varies by family member category. Young children and working adults suffer the greatest nutrition differential between harvest season and lean season, as given by the amplitude of the estimated sinusoid in the title of each sub-figure. This amplitude is about 40 percent larger for men than for women — driven by both a lower trough and a higher peak than experienced by women. Children in school suffer the least seasonal variation in BMI Z-scores. In fact, an F-test rejects the null hypothesis that all sinusoidal coefficients for children in school are zero only with marginally significance ($F=1.86$, $p$-value=0.11). An F-test of the same null hypothesis for older adults finds the sinusoidal terms to be insignificant at any confidence level, suggesting that older Tanzanian adults in farming families are not experiencing any real seasonality in nutritional status, despite their labor contribution to agriculture. These F-statistics are again listed in the title of the sub-figures.

Figure 6 illustrates the residual seasonality in nutritional status for each family member category, after controlling for (log) labor hours spent on agriculture in the last week, household dietary diversity score for the last week, or both, as in Equation 2. Table 3 provides the average marginal effect of these two mechanisms on nutritional status. Diet and labor expenditure are significantly associated with BMI Z-scores for both male and female working adults (Table 3 columns 3,4). Both factors also explain seasonality in nutritional status for these populations (Figure 6c,d). In fact, about half of the original, seasonal amplitude in nutritional status experienced by adult women is explained by these two factors, and residual seasonality becomes statistically insignificant upon controlling for both factors. Conversely, residual amplitude in the nutritional status of adult men, conditional on both controls, is 80 percent of the original amplitude for adult men, and still statistically significant.

Children in school contribute virtually no labor to agricultural activities, and so this control has no association with nutritional status and no explanatory effect on seasonality in nutritional status (Figure 6b, Table 3 column 2). Dietary diversity is positively associated with nutritional status for children in school, as with working adults, though the association is smaller in magnitude. Dietary diversity also explains the residual seasonality in nutritional status for children in school, and renders this seasonality insignificant, though not zero.

Notably, the nutritional status of young children is not affected by household dietary diversity score (Table 3 column 1), nor is seasonality in their nutritional status impacted by either control (Figure 6a). The amplitude of residual seasonality in BMI Z-scores for young children, conditional on both controls, is almost identical and in fact slightly larger than the original amplitude, and slightly more statistically significant.

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13 Table 3 holds the regressions that predict the black dots in Figure 6. However, sinusoidal coefficients are suppressed in Table 3 since they are visualized and more easily interpreted in Figure 6.
This suggests that household dietary diversity may be a poor proxy for the calorie and nutrient intake of young children.

While we do not include maize prices as a mechanism in our primary specification of Equation 2, due to non-random censoring of the data, we do so in Table A3. Median maize price in the enumeration area is positively associated with BMI Z-scores only for children in school and for adult males. Interpreting any change in residual seasonality is impossible however, given the change in sample population induced by data censoring. Similarly, we do not include non-agricultural labor as a mechanism in our primary specification. This is because it does not fluctuate cyclically with the agricultural season: Figure A10a illustrates that non-agricultural labor hours do not meet directly before and after Masika harvest as agricultural labor hours do. They do move cyclically with the calendar year, however, as shown in Figure A10b. However, if we do include non-agricultural labor in Equation 2, we find that it is positively associated with nutritional status for children in school and working adults (Table A4), but that it has no effect on residual seasonality in nutritional status for any type of family member (Figure A11). This makes sense since non-agricultural labor does not vary seasonally.

Last, we estimate Equation 3 and display the results in Figure 7 by predicting seasonal patterns for households at the 25th, 50th, and 75th percentile of log distance to markets. These households are labeled as close to, median distance from, and far from market, respectively, and we note the amplitude of the predicted function for each group. We also display the average marginal effect of distance to market on BMI Z-scores in Table 4. This direct effect is also incorporated in the sinusoids of Figure 7. We test for the joint significance of all four market interactions with sinusoidal terms; F-statistics are displayed in the bottom row of Table 4. The interactions are jointly significant only for male adults, though the average marginal effect of distance is significant also for adult women and for older adults.

For working-age adults and older adults, average nutritional status is higher for families closer to markets, and lowest for families farther from markets (Table 4, Columns 3-4). The same association is present, though of smaller magnitude and not significant, for children at school (Column 2). However, while average nutritional status does seem to vary with market access, seasonality in nutritional status does not change significantly with access to markets for any group except adult men. Working-age adult men experience more significantly seasonality in nutritional status when closer to market. This is precisely the opposite of what we might assume if proximity to market provides smoother access to diverse, healthy food. Working-age adult women experience approximately the same seasonality in nutritional status at any distance to market, and the same is true for children in school and for older adults.

It is striking that for children under eight, average nutritional status is higher when these children are located further from the market — though not significantly so. Additionally, seasonality in nutritional status is over 50 percent higher for young children close to markets than for young children far from markets, just as we observed in working age men. This shift is not statistically significant under our core specification, though it is statistically significant when distance is specified in binary terms according to median distance (Figure A12, Table A12). (Results for other groups are qualitatively and quantitatively similar under this specification.)
Taken together, these results provide no evidence that market access either improves nutritional status for young children in Tanzania or mitigates seasonality in their nutritional status. If anything, they provide some evidence for the opposite effect. While perhaps surprising in light of the literature showing increased dietary diversity with market access (a stylized fact that holds in our data as well), these last results align with our finding that increased dietary diversity at the household level does nothing to mitigate seasonality in child nutritional status (Figure 6 a).

5 Conclusion

We know that intra-household inequality contributes to poverty, and that malnourished individuals are not always found in generally poor and malnourished households (Brown, Ravallion and Van De Walle, 2017). But little is known about the intra-household differences in processes leading to malnutrition. It seems plausible that inputs to health are weighted differently for individuals with different roles within the household — for adults vs. children, or for women vs. men, or for individuals who spend most of their day on the farm vs. individuals who work or study outside of the household. We contribute new knowledge on this topic by examining how seasonal variability in nutritional status varies within the household, and additionally by examining how two mechanisms contribute to this seasonality for different types of household members. We do this by using a novel anthropometric measure – BMI Z-scores that can be calculated for household members of all ages – developed by Naschold (2018).

We find that seasonal variation in nutritional status for Tanzanian farming families is greatest for young children not in school and for working adults. Seasonal variation is less significant and lower for children in school, who are protected from agricultural labor activities and may access food differently than household members who spend their days on the farm. Seasonal variation is not significant for older adults. This suggests that older adults, who do still contribute agricultural labor hours, may be better compensated for their labor than are younger working adults, or may be engaged in less physically demanding agricultural activities.

We examine two mechanisms that seem likely to drive seasonality in nutritional status in our sample — household dietary diversity score, which serves as proxy for household diet quality more generally, and individual agricultural labor hours. Both mechanisms explain some part of the seasonality in nutritional status experienced by working adults. Neither young children nor children in school contribute hours to agricultural labor, so that mechanism is not expected to effect their nutritional status. However, it is notable that while dietary diversity does explain part of the muted seasonality experienced by school children, it does nothing to explain the more significant seasonality in the nutritional status experienced by young children not yet in school. This suggests that household-level dietary diversity may be a poor proxy for the quality of young children’s diets. Child-specific information on food intake may be necessary to understand seasonal fluctuation in child nutritional status. Alternatively, it may be that seasonality in the nutritional status of young children in Tanzania is explained by other cyclical factors, such as disease environment or parental care.

While access to markets is often found to increase nutritional status, it is not clear
whether it generally mitigates seasonal variation in nutritional status. If market integration weakens the linkage between production and consumption and improves access to diverse, healthy food during lean season, it might limit seasonality in nutritional status. Proximity to markets might also provide employment opportunities during lean season or improve the constancy of nutritional status in some other way.

However, we find that proximity to markets in rural Tanzania fails to mitigate the seasonality of nutritional status, even while it increases average nutritional status for adults. In fact, seasonality in the nutritional status of children is about 50 percent higher when those children live closer to markets. While this finding may be specific to Tanzania, similar evidence has been found elsewhere. While Hirvonon and Hoddinott (2017) find that market access mitigates the linkage between household production diversity and children’s dietary diversity in rural Ethiopia, Abay and Hirvonon (2017) find that seasonality in children’s weight-for-age is not significantly mitigated by market access in rural Ethiopia. Their results and our suggest that we do not understand the data generating process behind seasonality in the nutritional status of young children, despite the critical implications of this seasonality for long-term growth, cognitive development and later life productivity.
References


Figures

Figure (1) Agricultural cycle

Figure (2) Rainfall Totals by Month (ECMRWF)

Figure (3) Average Month to Begin Masika Harvest
Figure (4)  Household-level Seasonal Trends
Figure (5)  Seasonality in BMI Z-scores

Sub-figures according to $\alpha^c$, $\beta^c$, $\gamma^c$, $\delta^c$ estimated by Equation 1. Amplitude measures peak-to-trough difference, F provides the F-statistic for testing $\alpha^c = \beta^c = \gamma^c = \delta^c$, and Low provides the period of lowest nutritional status, measured in months.
Figure (6) Conditioning on Mechanisms: Residual Seasonality in BMI Z-scores

Sub-figures according to $\tilde{\alpha}_c$, $\tilde{\beta}_c$, $\tilde{\gamma}_c$, $\tilde{\delta}_c$ estimated by Equation 2. Gray dots provide baseline predictions from Equation 1, or from Equation 2 when $M_{rcyt}$ is empty. Blue dots provide predictions from Equation 2 including only agricultural hours or only dietary diversity in $M_{rcyt}$. Black dots provide predictions from Equation 2 once both variables are included in $M_{rcyt}$.
Figure (7) Distance to Market: Changes in BMI Z-score Seasonality

Sub-figures according to $\bar{\alpha}_c$, $\bar{\beta}_c$, $\bar{\gamma}_c$, $\bar{\delta}_c$, $\zeta$, $\bar{\alpha}_c$, $\bar{\beta}_c$, $\bar{\gamma}_c$, $\bar{\delta}_c$ estimated by Equation 3. Predictions given by the green, gray, and blue dots are evaluated at the 25th, 50th, and 75th percentile of $D_{rpt}$, respectively.
**Table (1) Summary Statistics (Means by Category)**

<table>
<thead>
<tr>
<th></th>
<th>Pre-school</th>
<th>Schooling</th>
<th>Female Adults</th>
<th>Male Adults</th>
<th>Elderly</th>
</tr>
</thead>
<tbody>
<tr>
<td>Female (binary)</td>
<td>0.49</td>
<td>0.52</td>
<td>1.00</td>
<td>0.00</td>
<td>0.49</td>
</tr>
<tr>
<td>Age at interview (years)</td>
<td>3.38</td>
<td>11.41</td>
<td>30.99</td>
<td>31.28</td>
<td>67.26</td>
</tr>
<tr>
<td>BMI Z-score (Z-score)</td>
<td>-0.27</td>
<td>-0.86</td>
<td>-0.42</td>
<td>-1.07</td>
<td>-1.12</td>
</tr>
<tr>
<td>Household dietary diversity score (#)</td>
<td>7.66</td>
<td>7.88</td>
<td>7.78</td>
<td>7.73</td>
<td>7.32</td>
</tr>
<tr>
<td>Any ag labor hours (binary)</td>
<td>0.03</td>
<td>0.26</td>
<td>0.67</td>
<td>0.70</td>
<td>0.60</td>
</tr>
<tr>
<td>Any non-ag labor hours (binary)</td>
<td>0.02</td>
<td>0.19</td>
<td>0.33</td>
<td>0.37</td>
<td>0.23</td>
</tr>
<tr>
<td>Non-ag labor hours (hours&gt;0)</td>
<td>8.35</td>
<td>13.46</td>
<td>31.84</td>
<td>34.10</td>
<td>27.36</td>
</tr>
<tr>
<td>EA-median maize flour price (log Tsh)</td>
<td>6.40</td>
<td>6.47</td>
<td>6.48</td>
<td>6.44</td>
<td>6.51</td>
</tr>
<tr>
<td>Distance from nearest regional market (log 100 km)</td>
<td>-0.32</td>
<td>-0.46</td>
<td>-0.43</td>
<td>-0.43</td>
<td>-0.51</td>
</tr>
<tr>
<td>Far from nearest regional market (&gt; 50th percentile)</td>
<td>0.55</td>
<td>0.48</td>
<td>0.51</td>
<td>0.51</td>
<td>0.45</td>
</tr>
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</table>

**Table (2) Seasonality in BMI Z-scores**

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Pre-school</td>
<td>Schooling</td>
<td>Female Adults</td>
<td>Male Adults</td>
<td>Elderly</td>
</tr>
<tr>
<td><strong>cos(2πt/τ₁)</strong></td>
<td>0.0377**</td>
<td>0.0232*</td>
<td>0.0230*</td>
<td>-0.00815</td>
<td>0.0148</td>
</tr>
<tr>
<td></td>
<td>(0.0166)</td>
<td>(0.0119)</td>
<td>(0.0127)</td>
<td>(0.0153)</td>
<td>(0.0241)</td>
</tr>
<tr>
<td><strong>sin(2πt/τ₁)</strong></td>
<td>0.0240</td>
<td>0.0223*</td>
<td>0.0360***</td>
<td>0.0452***</td>
<td>-0.000701</td>
</tr>
<tr>
<td></td>
<td>(0.0176)</td>
<td>(0.0125)</td>
<td>(0.0136)</td>
<td>(0.0164)</td>
<td>(0.0271)</td>
</tr>
<tr>
<td><strong>cos(2πt/τ₂)</strong></td>
<td>0.0183</td>
<td>0.00513</td>
<td>-0.00659</td>
<td>0.0434***</td>
<td>0.0178</td>
</tr>
<tr>
<td></td>
<td>(0.0177)</td>
<td>(0.0126)</td>
<td>(0.0136)</td>
<td>(0.0164)</td>
<td>(0.0261)</td>
</tr>
<tr>
<td><strong>sin(2πt/τ₂)</strong></td>
<td>-0.0214</td>
<td>0.00414</td>
<td>-0.0291**</td>
<td>-0.0301*</td>
<td>-0.0410</td>
</tr>
<tr>
<td></td>
<td>(0.0173)</td>
<td>(0.0124)</td>
<td>(0.0132)</td>
<td>(0.0160)</td>
<td>(0.0254)</td>
</tr>
<tr>
<td>Observations</td>
<td>10530</td>
<td>11465</td>
<td>10174</td>
<td>6612</td>
<td>3442</td>
</tr>
<tr>
<td>Between R²</td>
<td>0.0506</td>
<td>0.0829</td>
<td>0.0489</td>
<td>0.0614</td>
<td>0.0703</td>
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</tbody>
</table>

Regressions estimate Equation 1. Coefficients shown: $\alpha^c$, $\beta^c$, $\gamma^c$, $\delta^c$.
Region, survey year, and age-gender fixed effects are controlled for, as well as latitude and longitude.
p<0.01, ** p<0.05, * p<0.1

**Table (3) Conditioning on Mechanisms: Direct Effect of Mechanisms**

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Pre-school</td>
<td>Schooling</td>
<td>Female Adults</td>
<td>Male Adults</td>
<td>Elderly</td>
</tr>
<tr>
<td>Household dietary diversity score (#)</td>
<td>-0.00432</td>
<td>0.0396***</td>
<td>0.0778***</td>
<td>0.0681***</td>
<td>0.109***</td>
</tr>
<tr>
<td></td>
<td>(0.00725)</td>
<td>(0.00525)</td>
<td>(0.00551)</td>
<td>(0.00645)</td>
<td>(0.00969)</td>
</tr>
<tr>
<td>Ag labor hours (IHS hours)</td>
<td>0.00509</td>
<td>0.00138</td>
<td>-0.0318***</td>
<td>-0.0344***</td>
<td>-0.0578***</td>
</tr>
<tr>
<td></td>
<td>(0.0212)</td>
<td>(0.00648)</td>
<td>(0.00495)</td>
<td>(0.00572)</td>
<td>(0.00926)</td>
</tr>
<tr>
<td>Observations</td>
<td>10504</td>
<td>11446</td>
<td>10139</td>
<td>6549</td>
<td>3425</td>
</tr>
<tr>
<td>Between R²</td>
<td>0.0592</td>
<td>0.0876</td>
<td>0.0723</td>
<td>0.0835</td>
<td>0.115</td>
</tr>
</tbody>
</table>

Regressions estimate Equation 2. Only the $\phi$ coefficients are shown; sinusoidal coefficients are not shown.
Region, survey year, and age-gender fixed effects are controlled for, as well as latitude and longitude.
p<0.01, ** p<0.05, * p<0.1
Table (4) Distance to Market: Direct Effect of Distance

<table>
<thead>
<tr>
<th>Distance from nearest regional market (log 100 km)</th>
<th>(1) Pre-school</th>
<th>(2) Schooling</th>
<th>(3) Female Adults</th>
<th>(4) Male Adults</th>
<th>(5) Elderly</th>
</tr>
</thead>
<tbody>
<tr>
<td>Distance from nearest regional market (log 100 km)</td>
<td>0.0253 (0.0160)</td>
<td>-0.0161 (0.0102)</td>
<td>-0.0477 (0.0109)</td>
<td>-0.0937 (0.0130)</td>
<td>-0.0427 (0.0210)</td>
</tr>
<tr>
<td>Observations</td>
<td>10530</td>
<td>11465</td>
<td>10174</td>
<td>6612</td>
<td>3442</td>
</tr>
<tr>
<td>Between R2</td>
<td>0.0513</td>
<td>0.0836</td>
<td>0.0509</td>
<td>0.0718</td>
<td>0.0728</td>
</tr>
<tr>
<td>F-test ( \alpha = \beta = \gamma = \delta = 0 )</td>
<td>1.360</td>
<td>1.370</td>
<td>0.690</td>
<td>5.620</td>
<td>1.150</td>
</tr>
</tbody>
</table>

Regressions estimate Equation 3. Only \( \zeta \) is shown; coefficients on sinusoids and sinusoid-distance interactions are repressed. Region, survey year, and age-gender fixed effects are controlled for, as well as latitude and longitude. F-statistic tests the joint significance of all sinusoid-distance interactions.

\(< p < 0.01, \quad * * p < 0.05, \quad * p < 0.1 \)
Appendix A  Survey Timing

Figure (A1)  Interview Dates Round 1  Figure (A2)  Interview Dates Round 2

Figure (A3)  Interview Dates Round 3  Figure (A4)  Interview Dates Round 4
### Table (A1)  Parametric Check on Geographic Patterning in Survey Dates

<table>
<thead>
<tr>
<th></th>
<th>(1) Interview Month (All Rounds)</th>
<th>(2) Interview Month (Round 1)</th>
<th>(3) Interview Month (Round 2)</th>
<th>(4) Interview Month (Round 3)</th>
<th>(5) Interview Month (Round 4)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Latitude</strong></td>
<td>0.0466***</td>
<td>0.0616***</td>
<td>0.114***</td>
<td>0.0112</td>
<td>-0.0909***</td>
</tr>
<tr>
<td></td>
<td>(0.00689)</td>
<td>(0.0129)</td>
<td>(0.0125)</td>
<td>(0.0125)</td>
<td>(0.0190)</td>
</tr>
<tr>
<td><strong>Longitude</strong></td>
<td>0.102***</td>
<td>0.216***</td>
<td>0.185***</td>
<td>0.0453***</td>
<td>-0.142***</td>
</tr>
<tr>
<td></td>
<td>(0.00656)</td>
<td>(0.0126)</td>
<td>(0.0120)</td>
<td>(0.0121)</td>
<td>(0.0168)</td>
</tr>
<tr>
<td><strong>Observations</strong></td>
<td>43362</td>
<td>9625</td>
<td>12453</td>
<td>14602</td>
<td>6682</td>
</tr>
<tr>
<td><strong>R^2</strong></td>
<td>0.007</td>
<td>0.031</td>
<td>0.020</td>
<td>0.001</td>
<td>0.011</td>
</tr>
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</table>

*p<0.01, ** p<0.05, * p<0.1
Round fixed effects in column 1

### Table (A2)  Parametric Check on Geographic Patterning in Survey Dates

<table>
<thead>
<tr>
<th></th>
<th>(1) Interview Month (All Rounds)</th>
<th>(2) Interview Month (Round 1)</th>
<th>(3) Interview Month (Round 2)</th>
<th>(4) Interview Month (Round 3)</th>
<th>(5) Interview Month (Round 4)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Latitude</strong></td>
<td>0.120</td>
<td>-0.138</td>
<td>0.428*</td>
<td>0.0834</td>
<td>-0.145</td>
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<tr>
<td></td>
<td>(0.235)</td>
<td>(0.235)</td>
<td>(0.250)</td>
<td>(0.283)</td>
<td>(0.350)</td>
</tr>
<tr>
<td><strong>Longitude</strong></td>
<td>-0.0621</td>
<td>0.329</td>
<td>-0.0166</td>
<td>-0.0944</td>
<td>-0.461*</td>
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<tr>
<td></td>
<td>(0.154)</td>
<td>(0.207)</td>
<td>(0.200)</td>
<td>(0.224)</td>
<td>(0.266)</td>
</tr>
<tr>
<td><strong>Observations</strong></td>
<td>43362</td>
<td>9625</td>
<td>12453</td>
<td>14602</td>
<td>6682</td>
</tr>
<tr>
<td><strong>Within R^2</strong></td>
<td>0.00297</td>
<td>0.00528</td>
<td>0.0112</td>
<td>0.000654</td>
<td>0.0119</td>
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</table>

*p<0.01, ** p<0.05, * p<0.1
Round fixed effects in column 1
Region fixed effects in all columns
Appendix B  Household Gender Ratios

Figure (A5)  Seasonal Fluctuations in Household Gender Ratios (Non-parametric)

(a) Children < 8

(b) Children in School

(c) Non-schooling Adults

(d) Older Adults
Figure (A6)  BMI Z-score by age and gender

Figure (A7)  BMI Z-score by age and gender
Appendix C  Maize Flour Prices

Figure (A8)  Missing Data in the Log of EA-Median Maize Flour Prices

(a) Round 1

(b) Round 2

(c) Round 3

(d) Round 4
**Table (A3)**  Mechanisms: Including Maize Flour Prices

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Pre-school</td>
<td>Schooling</td>
<td>Male Adults</td>
<td>Female Adults</td>
<td>Elderly</td>
</tr>
<tr>
<td>Household dietary diversity score (#)</td>
<td>0.00102</td>
<td>0.0433***</td>
<td>0.0796***</td>
<td>0.0762***</td>
<td>0.104***</td>
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<tr>
<td></td>
<td>(0.00837)</td>
<td>(0.00596)</td>
<td>(0.00639)</td>
<td>(0.00758)</td>
<td>(0.0114)</td>
</tr>
<tr>
<td>Ag labor hours (IHS hours)</td>
<td>0.00167</td>
<td>0.00746</td>
<td>-0.0327***</td>
<td>-0.0431***</td>
<td>-0.0647***</td>
</tr>
<tr>
<td></td>
<td>(0.0251)</td>
<td>(0.00755)</td>
<td>(0.00573)</td>
<td>(0.00663)</td>
<td>(0.0107)</td>
</tr>
<tr>
<td>EA-median maize flour price (log Tsh)</td>
<td>0.00247</td>
<td>0.0624***</td>
<td>0.0410**</td>
<td>0.00220</td>
<td>0.0372</td>
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<td>(0.0245)</td>
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<td>(0.0188)</td>
<td>(0.0219)</td>
<td>(0.0363)</td>
</tr>
<tr>
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<td>8017</td>
<td>9061</td>
<td>7848</td>
<td>5032</td>
<td>2656</td>
</tr>
<tr>
<td>Between R2</td>
<td>0.0518</td>
<td>0.0860</td>
<td>0.0745</td>
<td>0.0856</td>
<td>0.121</td>
</tr>
<tr>
<td>Sinusoid F-stat</td>
<td>0.169</td>
<td>0.726</td>
<td>0.195</td>
<td>0.169</td>
<td>0.652</td>
</tr>
<tr>
<td>Sinusoid Amplitude</td>
<td>0.123</td>
<td>0.0450</td>
<td>0.0890</td>
<td>0.107</td>
<td>0.122</td>
</tr>
<tr>
<td>Low Point</td>
<td>243</td>
<td>110</td>
<td>206</td>
<td>72</td>
<td>37</td>
</tr>
</tbody>
</table>

p<0.01, ** p<0.05, * p<0.1
Appendix D  Non-Agricultural Labor

Figure (A10)  Time Trends in Non-Agricultural Labor (Non-parametric)

(a) According to Agricultural Season  
(b) According to Calendar Year

Table (A4)  Mechanisms: Including Non-Agricultural Labor

<table>
<thead>
<tr>
<th></th>
<th>(1) Pre-school</th>
<th>(2) Schooling</th>
<th>(3) Male Adults</th>
<th>(4) Female Adults</th>
<th>(5) Elderly</th>
</tr>
</thead>
<tbody>
<tr>
<td>Household dietary diversity score (#)</td>
<td>-0.00434 (0.00725)</td>
<td>0.0390*** (0.00525)</td>
<td>0.0768*** (0.00552)</td>
<td>0.0667*** (0.00647)</td>
<td>0.108*** (0.00969)</td>
</tr>
<tr>
<td>Ag labor hours (IHS hours)</td>
<td>0.00495 (0.0212)</td>
<td>0.0001114 (0.00649)</td>
<td>-0.0309*** (0.00496)</td>
<td>-0.0322*** (0.00579)</td>
<td>-0.0578*** (0.00926)</td>
</tr>
<tr>
<td>Non-ag labor hours (IHS hours)</td>
<td>0.0113 (0.0371)</td>
<td>0.0283*** (0.00944)</td>
<td>0.0180*** (0.00615)</td>
<td>0.0140** (0.00570)</td>
<td>0.0116 (0.0121)</td>
</tr>
</tbody>
</table>

Observations: 10504  11446  10139  6549  3425
Between R2: 0.0502  0.0883  0.0730  0.0844  0.115
Sinusoid F-stat: 0.0480  0.513  0.394  0.0130  0.443
Sinusoid Amplitude: 0.128  0.0470  0.0650  0.137  0.114
Low Point: 238  269  217  261  70

p<0.01, ** p<0.05, * p<0.1
Figure (A11) Seasonality Conditional on Non-Ag Labor

(a) Children < 8

(b) Children in School

(c) Adult women

(d) Adult men

(e) Older adults
Appendix E  Binary Specification of Distance

Figure (A12)  Seasonality in BMI Z-scores By (Binary) Distance to Market

(a) Children < 8  
(b) Children in School

(c) Adult women  
(d) Adult men

(e) Older adults
<table>
<thead>
<tr>
<th></th>
<th>(1) Pre-school</th>
<th>(2) Schooling</th>
<th>(3) Male Adults</th>
<th>(4) Female Adults</th>
<th>(5) Elderly</th>
</tr>
</thead>
<tbody>
<tr>
<td>Far from nearest regional market (&gt; 50th percentile)</td>
<td>0.0428</td>
<td>-0.00893</td>
<td>-0.0114</td>
<td>-0.0574**</td>
<td>0.0753*</td>
</tr>
<tr>
<td></td>
<td>(0.0264)</td>
<td>(0.0192)</td>
<td>(0.0205)</td>
<td>(0.0240)</td>
<td>(0.0399)</td>
</tr>
<tr>
<td>Observations</td>
<td>10530</td>
<td>11465</td>
<td>10174</td>
<td>6612</td>
<td>3442</td>
</tr>
<tr>
<td>Between R2</td>
<td>0.0518</td>
<td>0.0833</td>
<td>0.0496</td>
<td>0.0641</td>
<td>0.0742</td>
</tr>
<tr>
<td>F-test (market interactions)</td>
<td>3</td>
<td>1.120</td>
<td>1.880</td>
<td>3.290</td>
<td>2.390</td>
</tr>
</tbody>
</table>

p<0.01,  ** p<0.05,  * p<0.1