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Guilty Pleasures

Expenditure Elasticities of Ultra-Processed Foods and Paid Meals in India

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Abstract

The rising consumption of ultra-processed foods (UPFs) and paid food away from home (FAFH) is a growing concern for developing countries like India, which face the double burden of persistent malnutrition and increasing obesity. This paper examines the trends and drivers of UPF and paid meal consumption in rural and urban India from 2014 to 2019. Using high-frequency household consumption survey data, we estimate the expenditure elasticity of these food categories. Our results show a significant increase in the consumption of UPFs and paid meals over the study period. The expenditure elasticity of both UPF and FAFH exceeds 1 on average, indicating that they are highly responsive to income growth. Notably, poorer and urban households display higher elasticities compared to wealthier and rural households. Oaxaca-Blinder decomposition reveals that rising incomes and evolving dietary preferences contribute to the increase in UPF and paid meal consumption. These findings underscore the need for targeted interventions to promote healthier food choices, especially among lower-income groups, as India's economy continues to grow.

Keywords: Expenditure elasticity, paid meals outside home, ultra-processed foods, Engel curve, snacking, eating out

Abstract

This work was undertaken as part of the CGIAR Research Initiative on Transforming Agri-food Systems in South Asia (TAFSSA). TAFSSA aims to deliver a coordinated program of research and engagement across the food production-to-consumption continuum to support equitable access to sustainable healthy diets, improve farmer livelihoods and resilience, and conserve land, air and groundwater resources. Other CGIAR centers participating in TAFSSA include: CIMMYT, CIP, IRRI, and IWMI. We would like to thank all funders who supported this research through their contributions to the CGIAR Trust Fund: https://www.cgiar.org/funders/. Authors would like to thank ACIAR for its financial support to acquire the CPHS data under its short research activity (SRA) on Future of Food Systems in the Eastern Gangetic Plains.

Introduction

The consumption of calorie-dense, nutrient-poor ultra-processed foods (UPFs) and paid food away from home (FAFH) is growing rapidly in developing countries, raising public health concerns. UPFs are typically high in sugar, salt, and saturated fat and low in essential nutrients (Louzada et al. 2015; Jones et al. 2017; Martinez et al. 2017). Their regular consumption has been linked to rising obesity rates and an increased risk of developing various non-communicable diseases (Gulati et al. 2013; Arora et al. 2014; Joy et al. 2017; and Shrivastava et al. 2017). Similarly, rising consumption of FAFH is also associated with higher Body Mass Indices and poor health outcomes (Jiao et al. 2015). Understanding the drivers behind this shift is crucial for addressing public health challenges in countries like India that face double burden of persistently high levels of malnutrition and rising obesity rates.

This paper analyses the evolving trends in consumption of UPF and FAFH in rural and urban India. We explore three key research questions: What household characteristics are associated with increased spending on these food categories? How does the consumption of these food categories change with increase in per capita household expenditure? And what is the relative contribution of increasing household prosperity versus other unobserved factors to changing expenditure elasticities of consumption of both FAFH and UPD.

To answer these questions, we use high-frequency data from the Consumer Pyramids Household Survey (CPHS) collected by the Centre for Monitoring Indian Economy (CMIE) between 2014 and 2019. CPHS has data on monthly household expenditure on various food categories, as well as detailed demographic and socioeconomic characteristics of the households like household size, education, main occupations, and place of residence (rural or urban). We use linear probability models and parametric elasticity estimations and plot semi-parametric Engel curve to understand the patterns and drivers of UPF and FAFH consumption in rural and urban India. Additionally, we use an Oaxaca-Blinder decomposition to disentangle the impact of rising household expenditure (a surrogate measure for household income) on changes in budget allocations from other factors.

The CPHS data shows a significant increase in the consumption of UPFs and FAFH during the study period. The share of UPF in household food budgets increased from around 7.7% in 2015 to 10.2% in 2019**.** Similarly, the percentage of households reporting expenditure on paid meals increased by about 25 percentage points, from 60% to 85%, over this period while the budget

share increased from 3.5% to 4.3%. Total expenditure on FAFH increased from Rs. 619 billion ($9.2 billion) in 2015 to Rs. 820 billion ($12.2 billion) in 2019 (Table 1).

We use the Working-Lesser Model (WLM) to estimate expenditure elasticities and find that the consumption of UPFs and FAFH is highly responsive to changes in income proxied by household expenditure: with elasticities exceeding 1 for both categories. Expenditure elasticities for UPF and FAFH are greater among poorer households than wealthier ones, and higher for urban households compared to rural households. This implies that as incomes increase, lower-income and urban households are more likely to allocate a larger share of their additional income to UPF and FAFH consumption.

The Oaxaca-Blinder decomposition helps us disentangle the relative contributions of rising incomes from other unaccounted factors in driving the observed trends in the consumption of UPF and FAFH. While rising household expenditures account for a large portion of the increase in the share of UPF and FAFH in household budgets, a significant part of the shift is attributable to other unobserved factors. Shifts in dietary preferences and other external influences, such as changing food environments, specifically, increasing availability, accessibility, and convenience, of getting UPFs and paid meals, may be other drivers of these trends (Baker et al., 2020).

Several studies have looked at the prevalence of eating out in India and its correlates (Gaiha, Jha, and Kulkarni, 2013; Fiedler and Yadav, 2017; Kolady et al., 2021) and other developing countries (Liu et al., 2015; Farfan, Genoni and Vakis, 2017; Blick, Abidoye, and Kirsten, 2018; De Brauw and Herskowitz, 2021) and estimated expenditure elasticities of paid meals and ultra-processed or ultra-processed foods (Guerrero-Lopez et al., 2017; De Brauw and Herskowitz, 2021; John, Tullu, and Gupta, 2022). Many of these studies, especially, the ones from India, typically use cross-section data (e.g., Gaiha, Jha, and Kulkarni, 2013; Kolady et al., 2021) or low-frequency household surveys (e.g., John, Tullu, and Gupta, 2022), limiting their ability to capture the dynamic nature of dietary changes. These studies often had an urban focus (e.g., Guerrero-Lopez et al., 2017; Law et al., 2019; d'Amour et al, 2020; Liu et al., 2015).

Our paper contributes to the literature on dietary shifts in two ways. First, the CPHS data allows us to examine consumption trends in both rural and urban areas of India at a granular level and control for unobserved household-level factors that may influence food choices. We use high-frequency monthly consumption data and apply pooled sample analysis as well as panel data

methods, albeit for a smaller sample. Use of panel data allows us to control for unobserved factors like tastes and preferences that influence dietary choices. Our analysis of rural-urban differences and variations across income groups provides nuanced insights, earlier seen in studies like de Brauw and Herskowitz (2021).

Second, our results from the Oaxaca-Blinder decomposition shows some evidence that contrary to the common assumption, expenditure (or income) elasticity of UPF is not stable even over a relatively short period of time (5 years); it's increasing perhaps because of changing food environments that provide people more choices and easier access to ultra-processed and packaged foods in both rural and urban areas of India.

The rest of the paper is organized as follows. Section 2 describes the data used and presents the summary statistics on UPF and paid meal consumption in India. We discuss empirical methods and estimation strategy in Section 3 and results in Section 4. Section 5 concludes the paper.

1. Data and Summary Statistics

We use the Consumer Pyramids Household Survey (CPHS) data collected by the Centre for Monitoring the Indian Economy (CMIE) from April 2014 - December 2019 to analyze trends in consumption of FAFH and UPF. The CPHS covers a representative sample of almost 160,000 households across India. The sample is drawn based on a stratified multi-stage survey design where the primary sampling units are towns and villages from the Census 2011 data.

Each sampled household is interviewed thrice in a year in three waves where each wave spans four months.[i] In each wave, the CPHS collects month-wise recall data on household income and household consumption expenditure, detailing money spent on 80 different goods and services (including food, health, education, utility bills, recreation, remittances, EMIs, etc.). This data is collected from each household once in each wave but is reported for each month based on recall values. The CPHS also collects information on the employment status of all adult members in each of the calendar months since they were interviewed the last time.

The demographic module of the CPHS has information on the age, sex, education levels and occupation of all members of the household and the family's caste, religion, and domicile (migrant or born in the current location). We use the monthly recall data to create a high-frequency panel for our analysis in this paper. We analyze expenditure data on paid meals outside home (which includes meals consumed at restaurants, canteens, cafes and street

vendors) and UPFs which include – biscuits, salty snacks or "namkeen", noodles, pasta and flakes, ready-to-eat foods (semi-prepared with preservatives), "mithai" or Indian sweets, dry fruits, chocolates, cakes, ice creams, aerated beverages, and canned juices that are either fried in oil and/or high in salt or sugar content.

CPHS only reports total expenditure on paid meals and UPFs; it does not collect data on the quantity or frequency of consumption, or the prices or unit values of each purchase. Therefore, we cannot estimate price elasticities or the elasticities of substitution. Nor can we discern if a family's higher expenditure on a food group is because they are buying larger quantities or more expensive types of it. Additionally, not all ultra-processed foods are unhealthy, but CPHS does not capture information on the quality or nutritional content of foods. Hence, we limit our analysis to ultra-processed foods that are unhealthy and high in calorie content.

The attrition rate across waves in CPHS is high: of the 160 thousand households, only 32,708 (18%) have remained in the panel throughout this period. Of these, 24,485 households reside in urban areas and 8,223 in rural areas. Given the high attrition rate, we analyze the data as repeated cross-sections (N = 177,296 unique households), but also use panel data analyses with household fixed effects for the sub-sample of 32,708 households that stayed in the panel for the whole period. While this high attrition implies that the panel sub-sample may not be representative nationally, we find that the summary statistics for the full sample (Table 2) and panel sample (Table A.1) are similar.

CPHS collects data on both household incomes and consumption expenditure. However, given the high variance in income values reported in household surveys (Deaton 1997), we use monthly household expenditure as our main dependent variable while calculating elasticities. Results of the same analyses using monthly household income are reported in Tables A2.1 and A2.2 in the appendix to the paper.

Figures 1a to 1d depict trends in per capita expenditure on FAFH, UPF, fruits, and vegetables from March 2014 to March 2020 up to the first Covid-19 lockdown in India. All values reported in 2014 real prices. Separate trends for rural and urban sub-samples are plotted, and significant policy changes like demonetization (November 2016) and the introduction of the Goods and Service Tax (July 2017) are shown using vertical red lines. Similarly, figure 2a-d presents trends in the share of paid meals, ultra-processed foods, fruits, and vegetables in food expenditure across this period. Figures 3a to 3d show trends in the number of households that report spending monthly on these food categories across the years. The actual expenditure on

FAFH and UPF increased quite substantially from 2014 to 2019 with paid meal expenses rising by almost 50% in real terms for rural households and by 30% for urban households. The share of ultra-processed foods in food expenditure nearly doubles from 6% in 2014 to 11% in 2019 in rural areas and from 8% to 12% in urban areas. For the same period, we see a decline in the share of vegetables in the food budget (from 17% to 15% for urban areas and 18% to 16.5% in rural areas). It's possible that the increasing expenditure on paid meals and UPF is crowding out expenditure on healthy foods. However, in the absence of price and quantity data, we cannot formally test for this. More than 90% of households report buying ultra-processed foods consistently from 2014-2019; the percentage of households that reported non-zero expenditure on FAFH increased by 25 percentage points (from 60% to 85%) in this period. Thus, there has been a sharp increase in the consumption of FAFH at both at both the extensive and intensive margins. Consumption of UPF, already universal, also increased, but mostly at the intensive margin.

Table 2 presents summary statistics on household demographic and expenditure variables from our data. The average household size is 4 (3.8 for urban and 4.2 for rural households) and the average monthly household incomes for urban and rural households are Rs. 25353 and Rs. 15947 respectively. Households spend roughly half their disposable income on food, one-fifth of which is spent on fruits and vegetables. Ultra-processed food at home and paid meals outside account for nearly 13% of food expenses. 11% of households in our sample report both spouses working while 10% of households report hiring domestic help (18% in urban and 6% in rural areas).

Table 3 shows summary statistics on spending on various food categories across monthly per capita expenditure (MPCE) decile classes for both rural and urban households. For both rural and urban households, the share of food expenses in consumption expenditure declines as income increases. Similarly, the share of cereal expenses is lower for rich households compared to poor households as predicted by Bennet's law. The budget share of FAFH, on the other hand, is almost 55-70% more when we go from the poorest to the richest households while spending on UPFs is higher by 13-32%. This could be because richer households eat out more often and consume more UPF; it is also possible that they consume more expensive prepared meals and UPFs.

2. Empirical Strategy

Our empirical analysis focuses on the three research questions: trends in the household expenditure on UPF and FAFH; household characteristics associated with higher expenditure; and expenditure elasticities of FAFH and UPF.

More than two-thirds (68-71%) of all households in the CPHS sample consumed paid meals outside their home every month in the period 2017-2019. We use a linear probability model (lpm) to identify household characteristics associated with consumption of paid meals. We do not carry out a similar analysis for UPF because almost all (> 90%) of all households in the sample report consumption of UPF.

Second, we are interested in estimating expenditure elasticity of FAFH and UPF consumption. We plot semi-parametric Engel curves using the Frisch-Waugh method to check if they are linear and use WLM to estimate expenditure elasticities for both the full sample (pooled data) and the sub-sample for which we have panel data. Panel data analysis allows us to control for household fixed effects. Third, we use the Oaxaca-Blinder decomposition to analyze relative contributions of changes in household total expenditure and other unobserved factors to the budget shares of FAFH and UPF between 2015 and 2019. The Oaxaca-Blinder decomposition further clarifies whether income growth or other unobserved factors are driving these changes.

In the following section, we present the key findings from our analysis. The results reveal a significant rise in both UPF and FAFH consumption over the study period, highlighting important trends that align with economic growth and changing household preferences.

3.1. *Incidence of paid meals consumption*

We analyse the factors that determine whether a household spends on paid meals or not using a Linear Probability Model in Equation (1)

$$(I)_{irt} = \beta_0 + \beta_1 logY_{irt} + \beta_2 logH_{irt} + \beta_3 X_{irt} + \beta_3 \gamma_t + \theta_r + \varepsilon_{irt} \quad (1)$$

Where $(I^k)_{irt}$ is a binary variable that takes on a value of 0 for zero consumption of paid meals outside home and a value of 1 for positive expenditures, Y_{irt} is the monthly household expenditure and H_{irt} is the household size.[1]

[1] Since more than 95% households report consuming ultra-processed foods monthly, we do not include our LPM analysis on ultra-processed foods. Results of the same are available on request.

X_{irt} is a matrix of household characteristics that includes number of women in the household, whether a household has children and/or elders, the marital status of the household head, number of earning members and whether the household has a woman earning member, religious and caste group the household identifies with, occupation and education group of majority members in the household, the asset wealth group, whether the household spends on fitness, domestic help, cooking fuel and remittances, and finally the geographical location of the household determined by the city size group and the national zone (north, south, east, west) it resides in.

γ_t controls for survey rounds linearly, allowing us to analyse the time trends in incidence of eating paid meals outside home. θ_r controls for regional or state fixed effects. This accounts for state level or cultural factors that may drive food consumption behaviour across India.

3.2. *Expenditure elasticities of FAFH and UPF*

We estimate the expenditure or income elasticity of expenditure on paid meals and UPF using pooled regressions as shown in Equation (2):

$$(Q^k)_{irt} = \beta_0 + \beta_1 logY_{irt} + \beta_2 logH_{irt} + \beta_3 X_{irt} + \theta_r * \mu_t + \varepsilon_{irt} \quad (2)$$

Where Q^k is the expenditure on food category *k*, that is, UPFs or paid meals by household *i* in region *r* in survey round *t* and Y_{irt} is the monthly household expenditure. We include household size (H_{irt}) in log form to account for economies of scale and their impact on food demand (Bhalotra and Attfield, 1998).

X_{irt} is a matrix of household compositional variables that delineate age gender groups within the family (young boys and girls <15 years, adult men and women (15-60 years), and elder men and women (>60 years)). It also includes binary variables that capture whether a household has domestic help and an earning woman member. Lastly, it controls for the number of earning members in the family.

Following Bellemare, Barrett and Just (2013) and de Brauw and Herskowitz (2021), we use geographic area by survey round fixed effects ($\theta_r * \mu_t$) as a proxy for full set of local prices.

We also run panel regressions on the subset of households across this period (Equation 3), controlling for household size (H_{irt}) in log form, as before, and household fixed effects (δ_i) to account for all unobserved time-invariant household characteristics, tastes and preferences that could affect food consumption decisions.

$$Q^{k}{}_{i(r),t} = \beta_0 + \beta_1 logY_{i(r),t} + \beta_2 logH_{i(r),t} + \theta_r * \mu_t + \delta_i + \varepsilon_{i(r),t} \quad (3)$$

We estimate our model using the Working Leser Model following de Brauw and Herskowitz (2021). This functional form is a modified version of the Working (1943) form of an Engel curve. The outcome variable in this specification is $s^{k}_{i(r),t}$, that is, the share of food expense on category *k* (ultra-processed foods or paid meals) and the income elasticity is measured using Equation (4) as:

$$e_y^k = 1 + \frac{\beta_1}{\bar{s}^k_{i(r),t}} \quad (4)$$

This elasticity can be interpreted as the percent change in the food share of paid meals outside home/ultra-processed foods when total household expenditure rises by 1%, holding all other factors constant. The advantages of this model are that using budget shares instead of actual expenditure as the dependent variable ensures they are protected from errors in mismeasuring inflation given that they are in ratio form.

We also estimated expenditure elasticities using LLM, but WLM is our preferred model because unlike LLM, it allows for expenditure elasticity to change as household income or per capita expenditure changes.

Engel curves

WLM assumes a log-linear relationship between household expenditure and food share spent on paid meals/ultra-processed foods. We use a Frisch-Waugh Model to graphically analyse the relationship between total household expenditure and food share spent on ultra-processed foods and paid meals semi-parametrically to ensure that the data fits this functional form. Using the covariates from our pooled estimation and the household fixed effects from our panel regressions, we separately residualize both the budget shares and the log of household expenditure in stage one. In the second stage, we graph the relationship between the residual variation in the food budget shares and the residual variation in the log of household expenditure using a local polynomial estimation. This approach allows us to trace the functional form of the relationship across different values of expenditure and confirms that we have not erroneously excluded polynomial terms in our specification for the household expenditure variable on the LHS in elasticity estimation.

3.3.*Oaxaca-Blinder decomposition*

One key assumption in our model to measure elasticities is that preferences are stable across time. That is, while income levels and consumption levels may change, the model parameters (expenditure elasticity of food share on paid meals outside home/ ultra-processed foods) remain fixed. However, the evidence from our trend graphs in Figure 1, 2 and 3 challenges this assumption. Hence, we run cross-sectional and Oaxaca-Blinder Decomposition regressions on data from 2015 and 2019 to parametrically test whether there is a significant difference in elasticity estimations across time and how much of that variation can be explained by initial levels of explanatory variables.

We run our model in Equation (2) for the years 2015 and 2019 separately for two sample sets. In the first case, we use cross-sectional data across the two years. In the second case, we only include households for which we have data for both years. We then employ an Oaxaca-blinder twofold decomposition model to analyse if the difference in mean predicted share values of paid meals and ultra-processed foods in food budget are significant across the two periods and if so, how much of that difference is due to different levels of expenditure viz-a-viz different preferences or elasticities of expenditure. Our model is the same as Equation (3), with one addition that *year* takes on the value of 2015 or 2019.

$$S^{k}_{i(r),year} = \beta_0 + \beta_1 logY_{i(r),year} + \beta_2 logH_{i(r),year} + \beta_3 X_{i(r),year} + \theta_r * \mu_t + \varepsilon_{i(r),year} \quad (5)$$

If we consider E $[S^{k}_{2015}]$= E $[X'_{2015}\beta_{2015}]$ since we assume E $[\varepsilon_{2015}]$=0

Then, following (Jann, 2008), the difference in the mean predicted values of share spends on *k* food categories gives us,

$$E[S^{k}_{2015}] - E[S^{k}_{2019}] = E[X'_{2015}\beta_{2015}] - E[X'_{2019}\beta_{2019}] \quad (6)$$

$$= [E(X_{2015}) - E(X_{2019})]'\beta^* + [E(X_{2015})'(\beta_{2015} - \beta^*) + E(X_{2019})'(\beta^* - \beta_{2019})]$$

= Explained + Unexplained Portion of the Difference (Q + U)

Where Q, is part of the outcome differential that is “explained” by group differences in the predictors (“quantity or endowment effect”) and U is the “unexplained part” of the difference which is attributed to the differential effect of coefficients and their interaction with the endowments of predictors.

[β^* is a vector of coefficients that determines the contribution of different predictors in the model]

3. Results

We begin this section by presenting the correlates of the incidence of eating out, that is, the probability that a household spends on paid meals away from home. We then present estimations of expenditure elasticities for the share of paid meals and ultra-processed foods in food budgets, comparing our results across rural-urban and wealthy-poor subsamples as well. We complement these results with semi-parametric Engel curves using the Frisch-Waugh Method to establish that the relationship between household consumption expenditure and share of paid meals and ultra-processed foods is, indeed, linear. Finally, we provide evidence of changing trends in share of food budget spent on paid meals and ultra-processed foods from 2015 to 2019 using an Oaxaca decomposition model.

3.1 Probability of eating out and consuming ultra-processed foods

Table 4 presents results from a linear probability model that analyses the factors that influence a household's decision to consume paid meals away from home. The outcome variable is binary and coded as 1 for households that report non-zero expenditures on meals outside of home in each month and 0 otherwise. Similar analysis for ultra-processed food is included in the Appendix although over 95% households report spending on this food category and hence the LPM for the same is redundant.

Wealth: Households with higher monthly consumption expenditure are significantly more likely to eat at restaurants/food stalls. Surprisingly, households with a higher number of earning members are less likely to consume paid meals.

Household composition: Larger household size is associated with lower probabilities of consuming food FAFH. The higher the proportion of women in the household, the lower is the probability to eat out which could indicate that women make more nutritious choices (Boek et al., 2012; Beardsworth et al., 2002; Wardle et al., 2004) or that women are more likely to cook and provide meals at home. In India, household chores are generally delegated to women and their absence may induce the need to substitute home-cooked meals with eating out. Surprisingly, having a domestic help is positively correlated with the probability of eating out though this may be an income effect as hiring domestic help is characteristic of upper echelons

of society. Households that have cooking fuel expenses and indulge in pro-health behaviour like exercise and fitness are less likely to eat out.

Time trend: We also find that the incidence of eating out is rising with time at an increasing rate. We formally test for changing trends in Section 4.4.

Semi Parametric Engel Curves

To ascertain whether our assumption of linearity between consumption expenditure and food share spends on paid meals and ultra-processed foods is accurate, we estimate semi-parametric Engel curves using the Frisch-Waugh Method (Figures 5.1 and 5.2). For both cross sectional and panel specifications we find that the relationship between residualized budget shares of paid meals and ultra-processed food expenses and residualized log of household consumption expenditure is linear and has a positive slope.

3.2 Expenditure Elasticity of Paid Meals Outside Home and Ultra-processed Food Consumption

Households in our sample, on average, spend 3-5% of their food budget (Rs. 235) on FAFH (Table 2) and 9-10% of its food budget (Rs. 582) on UPFs (Table 2). We estimate the expenditure elasticity of these expenses for the whole sample and then separately for urban and rural households. We also estimate elasticities separately for households in the top and bottom quintiles of monthly per capita consumption expenditure (MPCE). Table 5.1 presents the parametric estimations from cross-sectional regressions using the Working Leser Model with share values of paid meals and ultra-processed foods in the food budget as the outcome variable respectively. Table 5.2 reports the estimations using panel data from 2017-2019. Columns 2 and 3 of both tables report results for rural and urban sub-samples, respectively, while Columns 4 and 5 report results for households in the bottom and top quintiles of MPCE. We include an interaction of state fixed effects and survey round time fixed effects as a proxy for local prices and their variation over time in both specifications.

Across all specifications, the expenditure elasticities of the share of food budget spent on both FAFH and UPF are greater than 1. The elasticity is higher for urban households compared to rural households. When we compare households across the bottom and top MPCE quintiles, we find that the elasticity is greater for the poorer households compared to the richer ones.

Richer families tend to spend a greater portion of their disposable income on eating out when they earn more or that they switch to better quality/more expensive restaurants when their

income rises.

We find similar elasticity estimates when we focus on our panel sample of households (32,708) across 2017-2019, controlling for household fixed effects (Table 5.2). In this specification, the difference in elasticities between poor and wealthy households is even more pronounced.

Results from both Linear-Log Model and Working-Leser Model show positive and statistically significant relationships between household expenditure and spending on paid meals and ultra-processed foods. The Linear-Log Model generally produces slightly lower elasticity estimates compared to the Working-Leser Model. However, the differences are not substantial, and both models indicate elastic demand (elasticity > 1) for paid meals and ultra-processed foods. Both models show higher elasticities for urban households compared to rural households for both paid meals and ultra-processed foods. The pattern of higher elasticities for poorer households compared to wealthier ones is maintained in both models. The panel data analysis results from both models are also similar, showing consistent patterns in elasticity estimates when controlling for household fixed effects. Thus, the demand for paid meals and ultra-processed foods is elastic across all model specifications and sub-samples. The patterns of elasticity differences between rural-urban and poor-rich households are also consistent across both models and the key variables maintain their statistical significance across both model specifications.

4.4. *Comparing expenditure elasticities with other countries*

Our elasticity estimates are similar to those in other developing countries. Ma et al., (2006) find a 1.76 expenditure elasticity for food consumed away from home (FAFH) in urban China using cross-sectional data; Shamsudin et al., (2009) estimate expenditure elasticity of 0.9 for FAFH in Malaysia using a Working-Leser Model, and de Brauw and Herskowitz (2021) estimate expenditure elasticity of 1.065 for highly processed foods consumed at home and 1.365 for FAFH in urban and rural Nigeria (table 6).

Our estimates of expenditure elasticities for paid meals and ultra-processed foods in India align with findings from other developing countries, while also revealing some unique patterns. Similar to studies in China (Ma et al., 2006) and Nigeria (de Brauw and Herskowitz, 2021), we find elastic demand for food away from home (FAFH) and ultra-processed foods, however, our estimates (ranging from 1.3 to 1.7) are generally higher than those found in Malaysia by Shamsudin et al. (2009).

The urban-rural differences, with higher elasticities in urban areas, are consistent with findings from China and Nigeria, reflecting the greater availability and variety of processed foods and eating-out options in urban settings across developing countries.

Our finding of higher elasticities for poorer and richer households contrasts with estimates from developed countries, such as Okrent and Alston (2012) in the United States, where elasticities tend to be lower for lower-income groups. This difference might reflect the transitional nature of food consumption patterns in India, where processed foods and eating out may still be seen as aspirational for lower-income households.

4.5 Oaxaca Blinder Decomposition

Table 7A compares the expenditure elasticities for paid meals between 2015 and 2019 using both the full sample (columns 1 and 2) and a panel sample (columns 3 and 4). The average share of paid meals increased from about 3.5% in 2015 to 4.3% in 2019 for the full sample, and from 3.4% to 4.1% for the panel sample. The elasticity for paid meals decreases slightly over time, from 1.75 in 2015 to 1.54 in 2019 for the full sample, and from 1.84 to 1.45 for the panel sample indicating that while households continue to increase their spending on paid meals as their income grows, the responsiveness to total expenditure (elasticity) has decreased over time. The Oaxaca-Blinder decomposition shows that for the full sample, the entire change in shares is explained by differences in predictor levels (endowments). However, for the panel sample, about 20% of the change remains unexplained, suggesting that other factors beyond changes in household characteristics, such as changes in preferences or external factors like food availability, may have influenced the increased share of paid meals. The positive coefficients for *log monthly household expenditure* indicate that higher-income households tend to spend a larger share of their food budget on paid meals.

Table 7B presents a similar analysis for the share of UPFs in food budgets. There was a somewhat bigger increase in the average share of ultra-processed foods, rising from about 7.7% in 2015 to 10.2% in 2019 for the full sample, and from 7.9% to 10.6% for the panel sample. The expenditure elasticity for ultra-processed foods also decreased, but more slowly than for paid meals, going from 1.65 to 1.46 in the full sample and 1.65 to 1.42 in the panel sample. This indicates that as incomes rise, households are still allocating more of their budget to ultra-processed foods, but the responsiveness to income changes has decreased over time. This could reflect a shift where ultra-processed foods, which were once more of a luxury, are becoming more commonplace or affordable across different income levels. For

UPFs, about 44% of the difference in mean share values remains unexplained and can be attributed to coefficients for the cross-sectional sample. When we focus on panel households, this ratio reduces to almost half (26%). The results from the cross-sectional sample may be driven by a change in the composition of the sample, that is, different households constituting the sample across periods which may be the reason we see a large change in preferences. But even when we examine the same set of households over time, we find that the unexplained portion is significant and larger than in the case of paid meals, suggesting that changes in preferences or other unobserved factors might play a more substantial role in shaping ultra-processed food consumption over time. The positive coefficients for *log monthly household expenditure* confirm that higher-income households tend to allocate a larger share of their food budget to ultra-processed foods.

The decomposition results suggest that our assumption of constant preferences when estimating elasticities does not hold true and we need to account for these changing trends when we study food choices and their relationship with income. Also, while both paid meals and ultra-processed foods show high expenditure elasticity, the underlying dynamics differ. For paid meals, the high elasticity appears stable, driven primarily by income effects. For ultra-processed foods, however, the high elasticity is compounded by shifting preferences or other unobserved factors, making these goods increasingly favored as incomes rise. These distinctions underscore the complexity of evolving food consumption patterns in India and highlights the need for multifaceted policy approaches to address associated health and economic implications. Specifically, effective policies for UPFs may need to consider broader cultural or preferential shifts in addition to income effects.

4. Discussion

Our analysis of Indian household data from 2014 to 2019 reveals several important trends and insights regarding the consumption of FAFH and UPF. Our findings reveal a substantial increase in the consumption of these food categories, driven by both rising incomes and other unaccounted factors. The high expenditure elasticity, particularly among lower-income groups, suggests that as India's economy continues to grow, the demand for UPFs and paid meals is likely to increase significantly. These trends pose challenges for public health and nutrition policy in India. The potential health risks associated with increased consumption of ultra-processed foods, combined with the existing burden of malnutrition, call for immediate and targeted policy interventions.

Both FAFH and UPF have high expenditure elasticities (around 1.4-1.5). Poorer households (bottom 20% MPCE) exhibit higher elasticity than wealthier households (top 20% MPCE). As households' incomes rise, they disproportionately increase their spending on these food categories and the poorest households are more likely to allocate a larger portion of their additional income to UPFs and paid meals.

Urban households show higher expenditure elasticity for both paid meals and ultra-processed foods compared to rural households. This could be due to greater availability and accessibility of these food options in urban areas, as well as differences in lifestyle and time constraints (Aiyar et al., 2021).

The Oaxaca-Blinder decomposition analysis reveals that rising incomes were not the only drivers of increase in consumption of these food categories between 2015 and 2019. A significant portion of the increase, particularly for ultra-processed foods, can be attributed to other unaccounted factors which may include changing food environment or changing preferences over time.

Factors such as household size, proportion of women, and the presence of domestic help influence the likelihood of consuming paid meals outside the home. This highlights the complex interplay between socio-economic factors and food consumption patterns.

These findings have important implications for public health, nutrition policy, and economic development in India. The high elasticity and increasing trend of UPF consumption raise concerns about potential negative health outcomes, particularly as India already faces a double burden of malnutrition and rising obesity rates. There is a need for targeted policy interventions to promote healthier food choices, especially among lower-income groups who show higher elasticity for UPFs and paid meals as their income rises. If changing preferences play a significant role in the increasing consumption of UPFs, then this underscores the importance of nutrition education and awareness campaigns to influence food choices positively. The higher elasticity in urban areas points to the need for policies that promote access to healthier food options and regulate the proliferation of fast-food outlets. The influence of household composition on food choices highlights the need for policies that consider gender roles and household dynamics in addressing nutrition issues. The high expenditure elasticity of UPFs and paid meals has implications for the food industry, agriculture sector, and overall economic development. As incomes rise, there may be a shift in demand away from traditional, unprocessed foods, potentially affecting local agriculture and food systems.

Despite multiple robustness checks, our analysis has several limitations. First, our analysis relies on expenditure data without corresponding information on quantities, prices, or nutrient profiles of the UPF and paid meals households consume. While we use geographic fixed effects to proxy for local prices, the lack of price data limits our understanding of the role of relative food prices in shaping dietary choices. We cannot estimate own and cross price elasticities between UPF and other food items, and test if the rising consumption of UPFs is crowding out consumption of more nutritious foods. Without price elasticity estimates, we are not able to assess the potential impact of sin taxes on consumption UPFs and FAFH in India either. Similarly, the absence of quantities and nutrient profiles of UPFs and FAFH restricts our ability to assess the health implications of the observed consumption patterns. Second, both UPF and FAFH include multiple food types that differ from one another in their responsiveness to changes expenditure (and prices), but our analysis treats UPFs and FAFH as composite groups and estimates aggregate expenditure elasticities of the composites. Demands for each individual product within the two categories may be more sensitive to income-induced changes in total expenditures than the aggregate UPF or FAFH group. Third, the high attrition rate in our panel data (only 18% of households present across all waves) may introduce some bias in our longitudinal analyses, although we found similar summary statistics between the full and panel samples. While we control for various household characteristics and use fixed effects in our panel analyses, there may be unobserved time-varying factors influencing food choices that our model does not capture. Fourth, the study period (2014-2019) precedes the COVID-19 pandemic and follows big economic shocks which has likely had significant impacts on food consumption patterns. The applicability of our findings to the post-pandemic context may be limited.

Notwithstanding these limitations, this study provides valuable insights into the changing patterns of ultra-processed food and paid meal consumption in India, offering a foundation for future research and policy discussions in this crucial area of public health and economic development.

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Tables and Figures

Table 1: Population Estimates of Real Annual Expenditure on paid meals outside home in India (2015-2019)

Year	Total Expenditure on Paid Meals outside home (in billion rupees)	Std. Error (in billion rupees)	[95% Conf. Interval] (in billion rupees)	
2015	619	0.981	617	621
2016	509	0.858	507	511
2017	570	0.907	568	572
2018	761	0.958	759	763
2019	820	0.951	818	822

Source: Authors' calculation based on CPHS data 2015-2019 published by CMIE, India

Table 2: Summary Statistics

2017-2019	*Full Sample*		*Urban Sample*		*Rural Sample*	
Variables	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Household Size	4.06	1.66	3.86	1.57	4.16	1.69
Monthly Consumption Expenditure (Rs.)	12011.01	8009.93	14258.78	9032.03	10890.67	7190.52
Monthly Income (Rs.)	19076.28	23207.72	25353.51	26978.02	15947.53	20368.09
Monthly Food Expenditure (Rs.)	5683.45	3109.09	6332.81	2630.31	5359.80	3274.32
Share of food in total expenditure (%)	51%	12%	48%	12%	53%	12%
Households report paid meal expenses	69%	46%	71%	45%	68%	47%
Share of paid meal in food expenses (%)	4%	4%	5%	5%	3%	3%
Monthly paid meal expenses (Rs.)	234.63	304.50	316.25	407.89	193.95	225.90
Households report ultra-processed food expenses	97%	18%	97%	17%	96%	18%
Share of ultra-processed food in food expenses (%)	9%	6%	10%	6%	9%	6%
Monthly ultra-processed food expenses (Rs.)	581.55	2070.67	710.48	639.54	517.30	2491.68
Households report vegetable expenses	100%	4%	100%	4%	100%	4%
Share of vegetables in food expenses (%)	16%	6%	16%	5%	17%	6%
Monthly vegetable expenses (Rs.)	647.85	404.68	716.49	450.52	613.64	375.11
Households report fruit expenses	83%	38%	87%	33%	80%	40%
Share of fruits in food expenses (%)	3%	2%	3%	2%	3%	2%
Monthly fruit expenses (Rs.)	182.19	173.28	217.28	189.68	164.71	161.68
Number of women members	1.92	1.06	1.84	1.00	1.96	1.08
Household has at least one child (0-15 years)	49%	50%	42%	49%	52%	50%
Household has at least one elder (>60 years)	22%	42%	25%	43%	21%	41%
Marital Status of Household Head (Married)	91%	29%	90%	30%	92%	28%
Number of earning members	1.33	0.73	1.25	0.72	1.37	0.73
At least one earning woman in multi-earner HH	11%	31%	9%	29%	12%	33%
Household Religion Group						
Hindu	87%	34%	84%	36%	88%	33%
Muslim	9%	29%	10%	31%	9%	28%
Household Caste Group						
General Caste	30%	46%	39%	49%	26%	44%
Other Backward Classes	40%	49%	39%	49%	41%	49%
Scheduled Caste	23%	42%	20%	40%	24%	43%
Scheduled Tribe	7%	25%	2%	15%	9%	28%
Education Group of majority members in Household						
Graduates	18%	39%	31%	46%	12%	33%
Matriculates	33%	47%	36%	48%	31%	46%
Literate	45%	50%	32%	46%	52%	50%
Illiterate	4%	19%	2%	13%	5%	22%
Occupation Group of majority members in Household						
Entrepreneurial Class	17%	37%	28%	45%	11%	32%
Salaried Class	20%	40%	36%	48%	13%	33%
Farmer Class	25%	43%	3%	16%	36%	48%
Daily Wage-Earning Class	29%	45%	21%	41%	33%	47%
Business + Salaried Class	2%	13%	3%	17%	1%	10%
Household Wealth Index Group [1=lowest]						
1	17%	37%	18%	39%	16%	37%
2	20%	40%	20%	40%	19%	40%
3	21%	41%	21%	41%	21%	41%
4	21%	41%	21%	41%	21%	41%
5	22%	41%	20%	40%	22%	42%

2017-2019	*Full Sample*		*Urban Sample*		*Rural Sample*	
Household spends on domestic help	10%	30%	18%	38%	6%	24%
Household spends on remittance	1%	9%	1%	10%	1%	9%
Household spends on fitness	1%	8%	2%	13%	0%	5%
Household spends on cooking fuel	79%	41%	78%	41%	81%	39%
Regional Zone Group						
Central	9%	28%	7%	25%	10%	30%
East	26%	44%	16%	37%	30%	46%
South	24%	43%	31%	46%	20%	40%
West	20%	40%	25%	43%	17%	38%
North	22%	41%	21%	41%	22%	42%
City Size Group						
Village	67%	47%			100%	0%
Small <20,000 households	13%	34%	39%	49%		
Medium (20,000-60,000 households)	5%	22%	15%	36%		
Large (60,000-200,000 households)	5%	21%	14%	34%		
Very Large (>200,000 households)	11%	31%	32%	47%		
N	177666		113884		63782	

Note: All values in the table above are weighted using CMIE All-India weights. Paid Meals include meals at restaurants, cafes, canteens, or street vendors. Ultra-processed foods include biscuits, salty snacks or "namkeen", noodles, pasta and flakes, ready-to-eat foods (semi-prepared with preservatives), "mithai" or Indian sweets, dry fruits, chocolates, cakes, ice creams, aerated beverages, and canned juices that are either fried in oil and/or high in salt or sugar content. The Wealth Index Group is assigned based on wealth rank calculated using Principal Component Analysis. The regional zones are assigned based on geographical location of states-Central (Chhattisgarh and Madhya Pradesh), East (Assam, Bihar, Jharkhand, Odisha and West Bengal), South (Andhra Pradesh, Karnataka, Kerala, Puducherry, Tamil Nadu and Telangana) and North (Delhi, Chandigarh, Haryana, Himachal Pradesh, Jammu & Kashmir, Punjab, Uttar Pradesh and Uttarakhand).

Table 3: Food Expenditure by Decile Classes of Monthly Per Capita Expenditure (MPCE) in Rural and Urban Areas of India (2017-2019)

	Rural Sample [N=113884]							**Urban Sample** [N=63782]						
Decile Class	Monthly per capita expenditure (MPCE) (In Rs.)	Share of food in total expenses (In %)	Share of cereals in food budget (In %)	Households that spend on paid meals outside home (Y/N)	Share of paid meals outside home in food budget (In %)	Households that spend on ultra-processed food (Y/N)	Share of ultra-processed food in food budget (In %)	Per capita monthly expenditure (In Rs.)	Share of food in total expenses (In %)	Share of cereals in food budget (In %)	Households that spend on paid meals outside home (Y/N)	Share of paid meals outside home in food budget (In %)	Households that spend on ultra-processed food (Y/N)	Share of ultra-processed food in food budget (In %)
1	1753.3	58.2%	28.1%	63.2%	2.9%	96.1%	8.2%	2297.94	54.7%	25.5%	64.3%	3.2%	96.2%	8.7%
2	2055.9	56.8%	27.1%	64.9%	2.9%	96.3%	8.3%	2770.77	52.4%	24.2%	65.4%	3.5%	96.6%	9.2%
3	2306.1	55.6%	26.2%	65.6%	3.0%	96.2%	8.5%	3119.77	50.9%	23.5%	66.2%	3.7%	96.6%	9.5%
4	2510.6	54.2%	25.7%	63.9%	3.1%	96.2%	8.6%	3465.37	49.8%	23.0%	67.3%	4.0%	96.4%	9.8%
5	2760.4	53.4%	25.1%	64.5%	3.2%	96.0%	8.7%	3797.79	48.8%	22.5%	67.9%	4.3%	96.3%	10.1%
6	2957.6	52.5%	24.5%	64.6%	3.3%	95.4%	8.8%	4164.69	47.8%	22.1%	68.5%	4.5%	96.4%	10.3%
7	3278.2	51.6%	23.9%	64.7%	3.5%	95.1%	9.0%	4545.40	46.9%	21.7%	68.5%	4.8%	96.1%	10.5%
8	3583.4	50.7%	23.5%	66.4%	3.7%	95.0%	9.0%	4985.14	45.8%	21.6%	68.6%	5.0%	96.0%	10.7%
9	4052.5	49.8%	22.9%	66.3%	3.9%	94.7%	9.1%	5617.46	44.6%	21.0%	70.0%	5.3%	95.9%	11.1%
10	4952.4	47.8%	22.0%	68.8%	4.5%	94.6%	9.3%	7014.95	42.4%	20.2%	67.4%	5.5%	96.3%	11.5%

Note: All values in the table above are weighted using CMIE All-India weights. Paid Meals include meals at restaurants, cafes, canteens, or street vendors. Ultra-processed foods include biscuits, salty snacks or “namkeen”, noodles, pasta and flakes, ready-to-eat foods (semi-prepared with preservatives), “mithai” or Indian sweets, dry fruits, chocolates, cakes, ice creams, aerated beverages, and canned juices that are either fried in oil and/or high in salt or sugar content. The decile classes are created using month per capita household expenditure.

Table 4: Linear Probability Regression on determinants of spending on paid meals outside home

Linear Probability Model	(1) Spends on Paid Meals Outside Home (Y/N)
Log Expenditure	0.220***
	(0.00879)
Log Household size	-0.0460***
	(0.00572)
Number of women in Household	-0.00539***
	(0.000981)
HH has at least one child (<=15 years)	0.00347*
	(0.00203)
HH has at least one elder member (>=60 years)	-0.00222
	(0.00221)
HH head is married	-0.0101**
	(0.00422)
HH has an earning woman	0.000536
	(0.00439)
Number of earning members in HH	-0.00733***
	(0.00167)
Religious Group (Base= Hindi)	
Muslim	-0.0207***
	(0.00726)
Others	0.0195**
	(0.00844)
Caste Category (Base=General)	
OBC	0.0144***
	(0.00412)
SC	0.00613
	(0.00510)
ST	-0.00582
	(0.00875)
Educational qualifications of majority members in HH (Base= Graduates)	
Matriculates	0.0123***
	(0.00271)
Literate	0.0206***
	(0.00358)
Illiterate	0.0232**
	(0.00899)
Occupation class of majority members in HH (Base=Entrepreneurial class)	
salaried class	-0.00952**
	(0.00427)
farmer class	-0.0308***
	(0.00452)
daily wage earner	-0.00680
	(0.00438)
Business + salaried	-0.00668
	(0.00701)
Others	-0.0400***
	(0.00533)
Wealth Index Rank (PCA) [Base=1]	
Rank 2	-0.00704
	(0.00458)
Rank 3	-0.0102*
	(0.00534)
Rank 4	-0.00331
	(0.00539)
Rank 5	-0.000658
	(0.00604)

Linear Probability Model	(1) Spends on Paid Meals Outside Home (Y/N)
HH spends on domestic help	0.0797***
	(0.0121)
HH has remittance expenses	-0.00760
	(0.0346)
HH spends on fitness	-0.0454**
	(0.0191)
HH spends on cooking fuel	-0.0252***
	(0.00455)
Regional Zone [Base=Central]	
East	0.000143
	(0.0203)
South	-0.161***
	(0.0211)
West	-0.204***
	(0.0201)
North	-0.00451
	(0.0224)
City Size [Base= Village]	
Small (<20,000 households)	0.00264
	(0.0161)
Medium (20,000-60,000 households)	0.0224
	(0.0157)
Large (60,000-200,000 households)	0.0152
	(0.0157)
Very Large (>200,000 households)	0.0156
	(0.0187)
Survey Round (Wave) [Base=Jan-April 2017]	
May-August, 2017	-0.00395
	(0.00696)
September-December, 2017	0.0134
	(0.00880)
Jan-April, 2018	0.0348***
	(0.00967)
May-August, 2018	0.0618***
	(0.0110)
September-December, 2018	0.0897***
	(0.0123)
Jan-April, 2019	0.0844***
	(0.0136)
May-August, 2019	0.0790***
	(0.0150)
September-December, 2019	0.132***
	(0.0149)
State FE	Yes
Observations	4,617,628
R-squared	0.226

Robust standard errors in parentheses clustered at PSU level
*** p<0.01, ** p<0.05, * p<0.1

Note: The results presented above are from a linear probability model that analyses the determinants of the likelihood that a family spends money on paid meals outside the house (Column 1). The outcome variables are binary and take on a value of 1 if a household had a non-zero expense on ultra-processed foods. The explanatory variables include log of total household monthly expenditure, log of household size, number of women in the household, binary variables for whether the household has a child (member <15 years), whether the household has an elder (member >60 years), whether the household head is married, and whether the household has an earning woman member. It also examines other demographic characteristics such as: number of earning members in the household, the religious and caste group the household, education qualifications of majority members in the household, occupation classification of majority members in the household, the wealth index rank (measured using Principal Component Analysis on the assets and amenities a household owns), the household having domestic help, spending on cooking fuel, sending remittance home and spending on fitness. Lastly, we control for geographical location of the household and include Regional and survey round fixed effects.

Table 5: Expenditure Elasticities using Share of Food Budget (Working Leser Model)

5.1: Cross Sectional Data (2017-2019)

A. Share of Paid Meals in Food Budget	(1) Full Sample	(2) Rural Sample	(3) Urban Sample	(4) p20 Sample	(5) p80 Sample
Average Share of Paid Meals in Food Budget	.0382262	.0348344	.0450349	.031949	.0519129
Calculated Expenditure Elasticity	1.51	1.40	1.54	1.55	1.44
Log Monthly Household Expenditure	0.0196***	0.0139***	0.0242***	0.0176***	0.0226***
	(0.00143)	(0.000452)	(0.00237)	(0.000593)	(0.00210)
Log Household Size	-0.00926***	-0.00671***	-0.0113***	-0.00817***	-0.00819***
	(0.000635)	(0.000464)	(0.00105)	(0.000663)	(0.00115)
Number of boys in HH (0-15 years)	-0.000214	-4.09e-06	-0.000691**	0.000124	-0.00165***
	(0.000132)	(0.000127)	(0.000328)	(0.000150)	(0.000475)
Number of girls in HH (0-15 years)	-9.21e-05	-6.30e-05	-0.000315	8.40e-05	-0.00155***
	(0.000118)	(0.000123)	(0.000294)	(0.000136)	(0.000508)
Number of adult women in HH (16-60 years)	-0.000400***	-0.000394***	-0.000605**	-0.000417***	-0.00122***
	(0.000118)	(0.000124)	(0.000281)	(0.000147)	(0.000462)
Number of adult men in HH (16-60 years)	-0.000249*	-0.000157	-0.000530	-0.000388**	-0.000700
	(0.000147)	(0.000131)	(0.000367)	(0.000167)	(0.000518)
Number of elder men in HH (>60 years)	-0.000340	-0.000481**	5.47e-05	-0.000563**	-0.000725
	(0.000238)	(0.000226)	(0.000514)	(0.000261)	(0.000734)
Number of elder women in HH (>60 years)	-0.000372	-0.000394	-0.000424	-0.000264	-0.00247***
	(0.000285)	(0.000244)	(0.000497)	(0.000280)	(0.000627)
Household has domestic help	0.0118***	0.00857***	0.00916***	0.00596***	0.0104***
	(0.00161)	(0.000756)	(0.00155)	(0.00112)	(0.00136)
Household has an earning woman member	-0.00101	0.000586	-0.000510	-0.000281	-0.00266**
	(0.000631)	(0.000363)	(0.000702)	(0.000382)	(0.00123)
Number of earning members in HH	-7.81e-05	0.000227	0.000905**	1.42e-05	0.000423
	(0.000150)	(0.000156)	(0.000396)	(0.000188)	(0.000584)
State * Survey Round FE	Yes	Yes	Yes	Yes	Yes
Household FE	No	No	No	No	No

Number of unique households	177296	63613	113683	42678	30167
Observations	4,617,628	1,564,419	3,053,209	1,154,728	750,770
R-squared	0.261	0.296	0.236	0.253	0.253

Robust standard errors in parentheses clustered at PSU level

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

Note: The regression coefficients presented in the table above are from cross-sectional regressions. The outcome variable is the share of paid meals outside home in food budget while the main variable of interest on the RHS is log of household monthly expenditure. Using average share values and regression coefficients we calculate the expenditure elasticity of share of paid meals outside home in food budget. Columns 1 denotes results for the whole sample, while Columns 2 and 3 denote results for rural and urban subsamples respectively. Columns 4 and 5 denote results for the households belonging to the bottom and top quintile expenditure classes respectively, that is, the bottom 20% and top 20% expenditure group households. All regressions are based on the Working-Leser Model results where the dependent variable is the share of food budget spent on paid meals outside home. In each regression we control for state into survey round fixed effects to account for price variations across space and time. We also control for log of household size to get per capita elasticities effectively and for other household composition and employment variables such as – number of young girls and boys, adult women and men, and elderly women and men in the household, whether the household has an earning woman member, whether the household has domestic help and the total number of earning members in the family. Elasticities calculated using the following formula: 1 + (beta_coefficient [Log_exp] / Average share of paid meals expense in food budget)

B. Share of Ultra-processed Foods in Food Budget	(1)	(2)	(3)	(4)	(5)
	Full Sample	Rural Sample	Urban Sample	p20 Sample	p80 Sample
Average Share of Ultra-processed Foods in Food Budget	.0950663	.0912135	.1028003	.0904385	.1044429
Calculated Expenditure Elasticity	1.45	1.41	1.46	1.47	1.41
Log Monthly Household Expenditure	0.0429***	0.0378***	0.0476***	0.0425***	0.0424***
	(0.000997)	(0.000858)	(0.00175)	(0.00110)	(0.00133)
Log Household Size	-0.00425***	-0.00268***	-0.00546***	-0.0105***	-0.00973***
	(0.000761)	(0.000880)	(0.00115)	(0.000986)	(0.00171)
Number of boys in HH (0-15 years)	0.00168***	0.00152***	0.00243***	0.00159***	0.00637***
	(0.000222)	(0.000244)	(0.000475)	(0.000267)	(0.000760)
Number of girls in HH (0-15 years)	0.00141***	0.00106***	0.00259***	0.00146***	0.00609***
	(0.000217)	(0.000239)	(0.000445)	(0.000256)	(0.000764)
Number of adult women in HH (16-60 years)	-0.00117***	-0.00149***	-0.000748**	-0.000949***	0.00170***
	(0.000198)	(0.000230)	(0.000347)	(0.000271)	(0.000569)
Number of adult men in HH (16-60 years)	-0.00220***	-0.00208***	-0.00236***	-0.00212***	0.00125**
	(0.000203)	(0.000240)	(0.000385)	(0.000289)	(0.000544)
Number of elder men in HH (>60 years)	-0.00609***	-0.00578***	-0.00595***	-0.00346***	-0.00500***
	(0.000351)	(0.000397)	(0.000582)	(0.000470)	(0.000760)
Number of elder women in HH (>60 years)	-0.00284***	-0.00289***	-0.00254***	-0.00279***	-0.000559
	(0.000327)	(0.000388)	(0.000590)	(0.000482)	(0.000812)
Household has domestic help	0.00932***	0.00954***	0.00459**	0.00449**	0.0113***
	(0.00164)	(0.00111)	(0.00228)	(0.00180)	(0.00167)
Household has an earning woman member	0.000155	0.00181***	0.000238	-0.00132**	0.00246**
	(0.000681)	(0.000551)	(0.000910)	(0.000665)	(0.00124)
Number of earning members in HH	-0.00254***	-0.00186***	-0.00242***	-0.00188***	-0.00329***
	(0.000241)	(0.000268)	(0.000387)	(0.000318)	(0.000703)
State * Survey Round FE	Yes	Yes	Yes	Yes	Yes
Household FE	No	No	No	No	No
Number of unique households	177296	63613	113683	42678	30167
Observations	4,617,628	1,564,419	3,053,209	1,154,728	750,770
R-squared	0.283	0.265	0.317	0.277	0.357

Robust standard errors in parentheses clustered at PSU level
*** p<0.01, ** p<0.05, * p<0.1

Note: The regression coefficients presented in the table above are from cross-sectional regressions. The outcome variable is the share of ultra-processed food in food budget while the main variable of interest on the RHS is log of household monthly expenditure. Using average share values and regression coefficients we calculate the expenditure elasticity of share of ultra-processed food home in food budget. Columns 1 denotes results for the whole sample, while Columns 2 and 3 denote results for rural and urban subsamples respectively. Columns 4 and 5 denote results for the households belonging

to the bottom and top quintile expenditure classes respectively, that is, the bottom 20% and top 20% expenditure group households. All regressions are based on the Working-Leser Model results where the dependent variable is the share of food budget spent on ultra-processed foods. In each regression we control for state into survey round fixed effects to account for price variations across space and time. We also control for log of household size to get per capita elasticities effectively and for other household composition and employment variables such as – number of young girls and boys, adult women and men, and elderly women and men in the household, whether the household has an earning woman member, whether the household has domestic help and the total number of earning members in the family. Elasticities calculated using the following formula: 1 + (beta_coefficient [Log_exp] / Average share of ultra-processed food expense in food budget)

5.2: Panel Data (2017-2019)

A. Share of Paid Meals in Food Budget	(1) Full Sample	(2) Rural Sample	(3) Urban Sample	(4) p20 Sample	(5) p80 Sample
Average Share of Paid Meals in Food Budget	.0371511	.0331568	.0431516	.0319325	.0506925
Calculated Expenditure Elasticity	1.40	1.37	1.42	1.57	1.29
Log Monthly Household Expenditure	0.0149***	0.0124***	0.0181***	0.0181***	0.0148***
	(0.000878)	(0.000889)	(0.00173)	(0.00101)	(0.00155)
Log Household Size	-0.00627***	-0.00516***	-0.00789***	-0.00757***	-0.00840***
	(0.000827)	(0.000982)	(0.00135)	(0.00107)	(0.00208)
State * Survey Round FE	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes
Number of unique households	32,708	8,223	24,485	9,277	4,600
Observations	1,177,488	296,028	881,460	333,972	165,600
R-squared	0.110	0.138	0.107	0.130	0.133

Robust standard errors in parentheses clustered at PSU level
*** p<0.01, ** p<0.05, * p<0.1

Note: The regression coefficients presented in the table above are from panel regressions. The outcome variable is the share of paid meals outside home in food budget while the main variable of interest on the RHS is log of household monthly expenditure. Using average share values and regression coefficients we calculate the expenditure elasticity of share of paid meals outside home in food budget. Columns 1 denotes results for the whole sample, while Columns 2 and 3 denote results for rural and urban subsamples respectively. Columns 4 and 5 denote results for the households belonging to the bottom and top quintile expenditure classes respectively, that is, the bottom 20% and top 20% expenditure group households. All regressions are based on the Working-Leser Model results where the dependent variable is the share of food budget spent on ultra-processed foods. In each regression we control for household fixed effects and state into survey round fixed effects to account for unobserved household heterogeneity and price variations across space and time. We also control for log of household size to get per capita elasticities effectively. Elasticities calculated using the following formula: 1 + (beta_coefficient [Log_exp] / Average share of paid meals expense in food budget)

B. Share of Ultra-processed Foods in Food Budget	(1) Full Sample	(2) Rural Sample	(3) Urban Sample	(4) p20 Sample	(5) p80 Sample
Average Share of Ultra-processed Foods in Food Budget	.0973774	.0927578	.1043169	.093332	.1086543
Calculated Expenditure Elasticity	1.44	1.43	1.44	1.48	1.35
Log Monthly Household Expenditure	0.0424*** (0.00125)	0.0398*** (0.00154)	0.0461*** (0.00200)	0.0451*** (0.00174)	0.0377*** (0.00218)
Log Household Size	-0.00359*** (0.00126)	-0.00297* (0.00166)	-0.00362** (0.00179)	-0.0105*** (0.00163)	0.000680 (0.00296)
State * Survey Round FE	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes
Number of unique households	32,708	8,223	24,485	9,277	4,600
Observations	1,177,488	296,028	881,460	333,972	165,600
R-squared	0.164	0.184	0.154	0.222	0.137

Robust standard errors in parentheses clustered at PSU level

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

Note: The regression coefficients presented in the table above are from panel regressions. The outcome variable is the share of ultra-processed foods in food budget while the main variable of interest on the RHS is log of household monthly expenditure. Using average share values and regression coefficients we calculate the expenditure elasticity of share of ultra-processed foods in food budget. Columns 1 denotes results for the whole sample, while Columns 2 and 3 denote results for rural and urban subsamples respectively. Columns 4 and 5 denote results for the households belonging to the bottom and top quintile expenditure classes respectively, that is, the bottom 20% and top 20% expenditure group households. All regressions are based on the Working-Leser Model results where the dependent variable is the share of food budget spent on ultra-processed foods. In each regression we control for household fixed effects and state into survey round fixed effects to account for unobserved household heterogeneity and price variations across space and time. We also control for log of household size to get per capita elasticities effectively. Elasticities calculated using the following formula: 1 + (beta_coefficient [Log_exp] / Average share of ultra-processed food expense in food budget)

Table 6. Estimates of expenditure elasticities for processed foods and FAFH across different countries

Study	Country	Food Category	Elasticity Estimate	Notes
Our study	India	Paid meals (FAFH)	1.5 - 1.7	Higher for urban and poorer households
Our study	India	Ultra-processed foods	1.3 - 1.5	Higher for urban and poorer households
Ma et al. (2006)	China	FAFH	1.76	Urban China, cross-sectional data
Shamsudin et al. (2009)	Malaysia	FAFH	0.9	Using Working-Leser Model
de Brauw and Herskowitz (2021)	Nigeria	Highly processed foods at home	1.065	Urban and rural Nigeria
de Brauw and Herskowitz (2021)	Nigeria	FAFH	1.365	Urban and rural Nigeria
Okrent and Alston (2012)	USA	FAFH	0.67 - 0.95	Lower for lower-income groups
Burggraf et al. (2015)	Russia	Convenience foods	0.62 - 1.18	Varies by product category

Table 7: Comparison of 2015 and 2019 expenditure elasticities (Oaxaca-Blinder decomposition analysis)

	Full Sample		Panel Sample	
A. Share of Paid Meals in Food Budget	(1)	(2)	(3)	(4)
	2015	2019	2015	2019
Average Share of Paid Meals in Food Budget	.0354786	.0432759	.0343777	.0409999
Calculated Expenditure Elasticity	**1.75**	**1.54**	**1.84**	**1.45**
Log Monthly Household Expenditure	0.0265***	0.0234***	0.0288***	0.0183***
	(0.00196)	(0.00213)	(0.00171)	(0.00185)
Log Household Size	-0.00869***	-0.0119***	-0.0117***	-0.0102***
	(0.000765)	(0.00104)	(0.00124)	(0.00137)
Number of boys in HH (0-15 years)	3.68e-05	-7.62e-05	0.000725*	-0.000781*
	(0.000279)	(0.000234)	(0.000376)	(0.000467)
Number of girls in HH (0-15 years)	0.000258	0.000124	0.000985**	9.46e-06
	(0.000250)	(0.000196)	(0.000392)	(0.000339)
Number of adult women in HH (16-60 years)	-0.000713***	-9.88e-05	-0.000324	0.000108
	(0.000239)	(0.000203)	(0.000401)	(0.000399)
Number of adult men in HH (16-60 years)	-0.000371	-0.000170	-3.95e-05	-1.59e-05
	(0.000257)	(0.000207)	(0.000378)	(0.000372)
Number of elder men in HH (>60 years)	-0.000149	0.000684**	4.59e-06	0.000618
	(0.000336)	(0.000337)	(0.000597)	(0.000593)
Number of elder women in HH (>60 years)	-0.000590*	0.000581	0.000103	0.00137
	(0.000357)	(0.000555)	(0.000672)	(0.000870)
State * Survey Round FE	Yes	Yes	Yes	Yes
Number of Households	158719	165787	32782	32782
Observations	1,432,616	1,601,690	393,375	393,371
R-squared	0.202	0.249	0.233	0.266
Oaxaca Decomposition Mean Predicted Values (Share of Paid Meals)	0.0355***	0.0433***	0.0774***	0.102***
	(0.000645)	(0.000885)	(0.00103)	(0.00114)
Difference between 2015 and 2019	-0.00780***		-0.0250***	
	(0.000968)		(0.00148)	
Explained Portion of Difference (Endowments)	-0.00863***		-0.0200***	
	(0.000708)		(0.000917)	
Unexplained Portion of Difference (Coefficients)	0.000832		-0.00500**	
	(0.00103)		(0.00198)	

Robust standard errors in parentheses clustered at PSU level
*** p<0.01, ** p<0.05, * p<0.1

Note: The regression coefficients presented in the table above are from a cross sectional regression that uses the household sample from 2015 and 2019 in the CMIE data. In column (1) and (2) the analysis uses the entire sample across the two periods, while in column (3) and (4), only the panel households across both years are included. The outcome variable is the share of paid meals outside home in food budget. The main explanatory variable is log of monthly household expenditure which is used to calculate expenditure elasticities across the models using average share values. In each regression we control for household composition variables such as log of household size, and the number of members across age and gender (young boys and girls, adult men and women, elder men, and women) and state into survey round fixed effects to account for price variations across space and time. After analysing the two periods separately, we employ an Oaxaca- Blinder Decomposition model (twofold) to examine what percentage of the change in share of paid meals in the food budget from 2015 to 2019 can be explained by endowments (difference in level of predictors) and how much remains unexplained (due to differences in coefficients of predictors). We find that for the cross-sectional sample, the change in shares is completely explained by the difference in levels of predictors but for the panel sample (same households across both periods), about 20% remains unexplained by levels of predictors. Elasticities calculated using the following formula: 1 + (beta_coefficient [Log_exp] / Average share of paid meals expense in food budget)

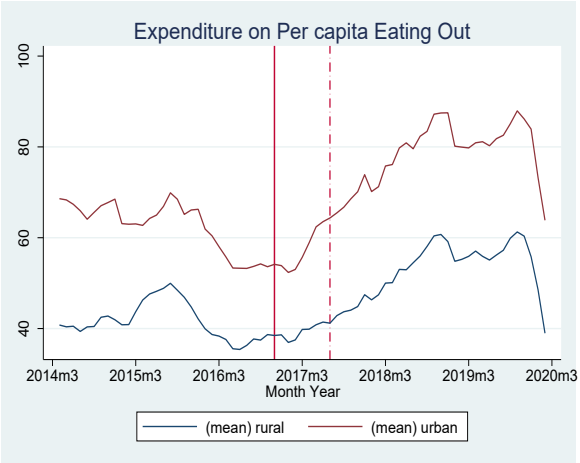
	Full Sample		Panel Sample	
B. Share of Ultra-processed Foods in Food Budget	(1)	(2)	(3)	(4)
	2015	2019	2015	2019
Average Share of Ultra-processed Food in Food Budget	.0774008	.1023832	.0791949	.1063883
Calculated Expenditure Elasticity	**1.65**	**1.46**	**1.65**	**1.42**
Log Monthly Household Expenditure	0.0505***	0.0467***	0.0517***	0.0448***
	(0.00205)	(0.00127)	(0.00219)	(0.00178)
Log Household Size	-0.0116***	-0.00535***	-0.0113***	-0.00619***
	(0.00105)	(0.000971)	(0.00158)	(0.00159)
Number of boys in HH (0-15 years)	0.00112***	0.00180***	0.000974**	0.00257***
	(0.000267)	(0.000290)	(0.000464)	(0.000556)
Number of girls in HH (0-15 years)	0.00115***	0.00149***	0.000897**	0.00134**
	(0.000245)	(0.000288)	(0.000433)	(0.000552)
Number of adult women in HH (16-60 years)	-0.00117***	-0.00157***	-0.000454	-0.00136***
	(0.000261)	(0.000261)	(0.000461)	(0.000517)
Number of adult men in HH (16-60 years)	-0.00299***	-0.00340***	-0.00283***	-0.00220***
	(0.000269)	(0.000257)	(0.000459)	(0.000481)
Number of elder men in HH (>60 years)	-0.00352***	-0.00679***	-0.00405***	-0.00559***
	(0.000419)	(0.000421)	(0.000745)	(0.000793)
Number of elder women in HH (>60 years)	-0.00118***	-0.00310***	9.45e-05	-0.00287***
	(0.000447)	(0.000433)	(0.000839)	(0.000816)
State * Survey Round FE	Yes	Yes	Yes	Yes
Number of Households	158719	165787	32782	32782
Observations	1,432,616	1,601,690	393,375	393,371
R-squared	0.286	0.312	0.306	0.315
Oaxaca Decomposition Mean Predicted Values	0.0344***	0.0410***	0.0792***	0.106***
(Share of Ultra-processed Foods)	(0.000886)	(0.00101)	(0.00139)	(0.00139)
Difference between 2015 and 2019	-0.00662***		-0.0272***	
	(0.00107)		(0.00184)	
Explained Portion of Difference (Endowments)	-0.00954***		-0.0202***	
	(0.000675)		(0.00123)	
Unexplained Portion of Difference (Coefficients)	0.00292***		-0.00697***	
	(0.00109)		(0.00242)	

Robust standard errors in parentheses clustered at PSU level
*** p<0.01, ** p<0.05, * p<0.1

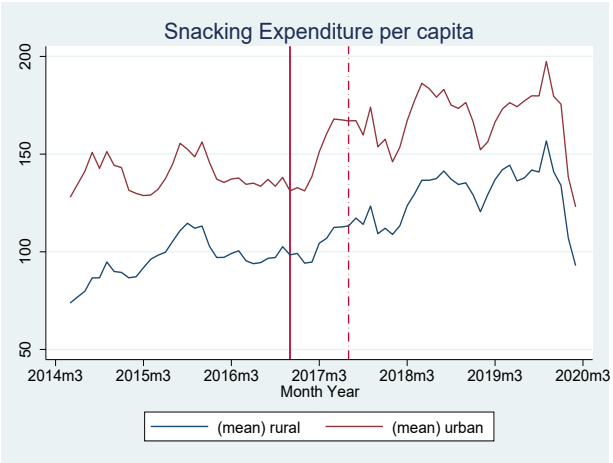
Note: The regression coefficients presented in the table above are from a cross sectional regression that uses the household sample from 2015 and 2019 in the CMIE data. In column (1) and (2) the analysis uses the entire sample across the two periods, while in column (3) and (4), only the panel households across both years are included. The outcome variable is the share of paid meals outside home in food budget. The main explanatory variable is log of monthly household expenditure which is used to calculate expenditure elasticities across the models using average share values. In each regression we control for household composition variables such as log of household size, and the number of members across age and gender (young boys and girls, adult men and women, elder men, and women) and state into survey round fixed effects to account for price variations across space and time. After analysing the two periods separately, we employ an Oaxaca- Blinder Decomposition model (twofold) to examine what percentage of the change in share of paid meals in the food budget from 2015 to 2019 can be explained by endowments (difference in level of predictors) and how much remains unexplained (due to differences in coefficients of predictors). We find that for the cross-sectional sample, about 44% remains unexplained by endowments and for the panel sample (same households across both periods), about 26% remains unexplained by levels of predictors. Elasticities calculated using the following formula: 1 + (beta_coefficient [Log_exp] / Average share of ultra-processed food expense in food budget)

Figure 1: Trends in per capita expenditure (Rs.)

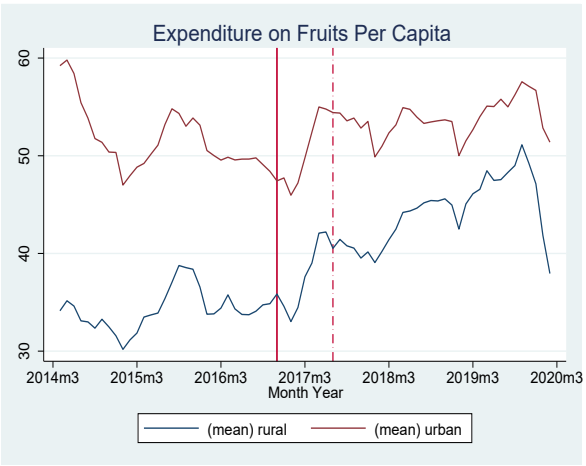
a. Paid Meals Outside Home



b. Ultra-processed foods (snacks)



c. Fruits



d. Vegetables

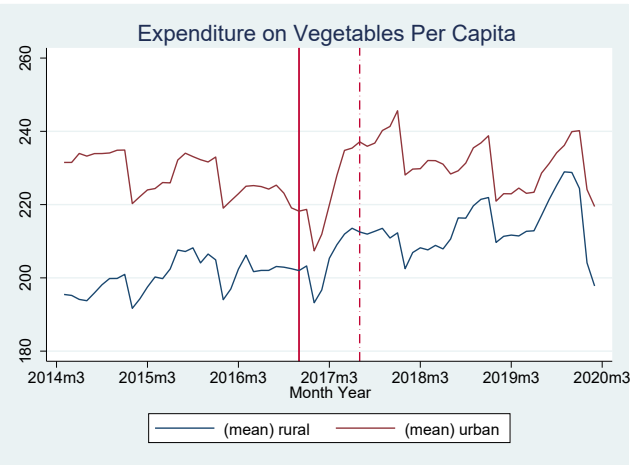
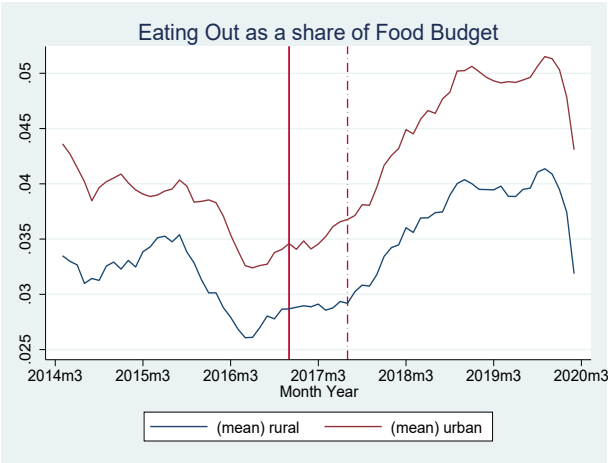
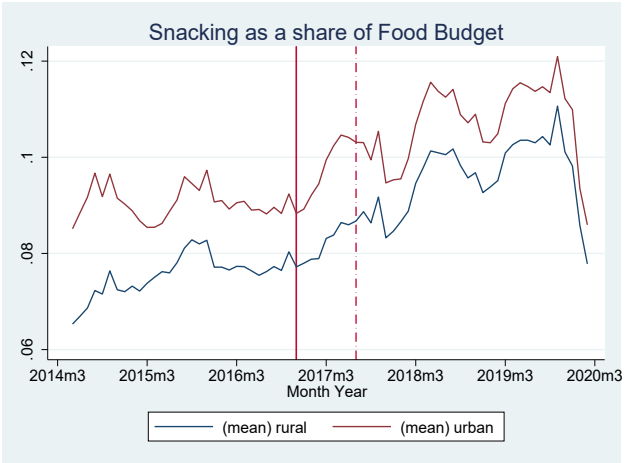


Figure 2: Trends in share of item in food budget

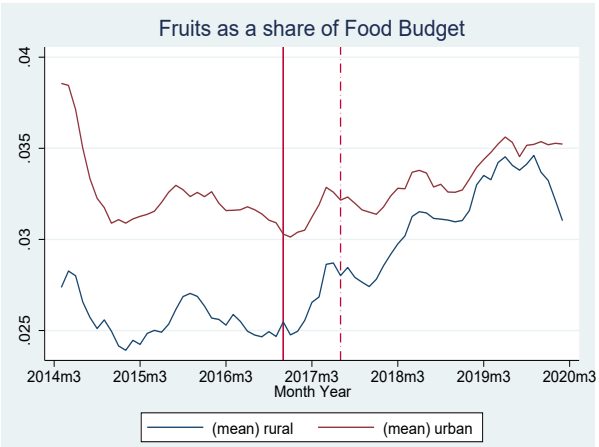
a. Paid Meals Outside Home



b. Ultra-processed foods (snacks)



c. Fruits



d. Vegetables

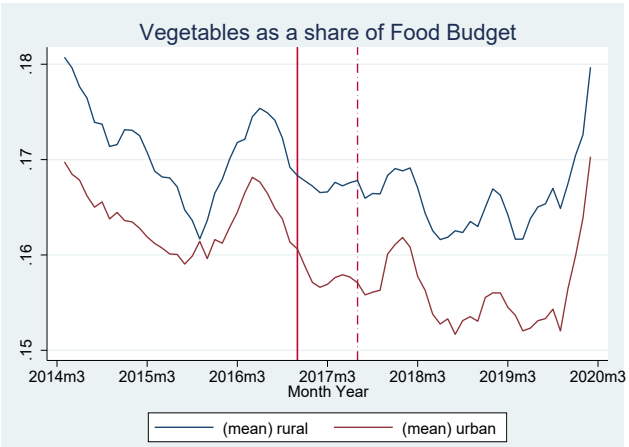
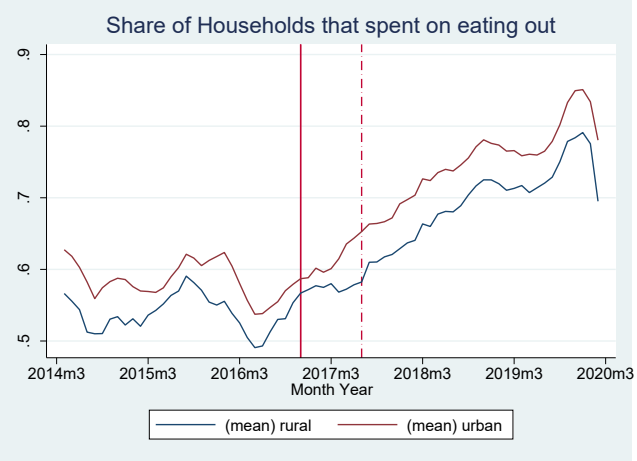
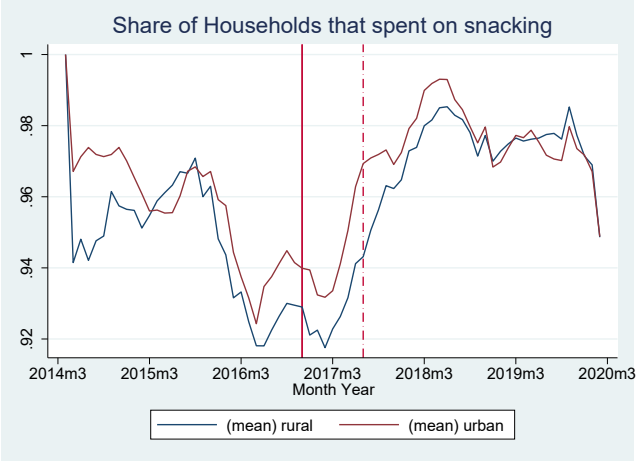


Figure 3: Trends in percentage of households reporting non-zero expenditure

a. Paid Meals Outside Home

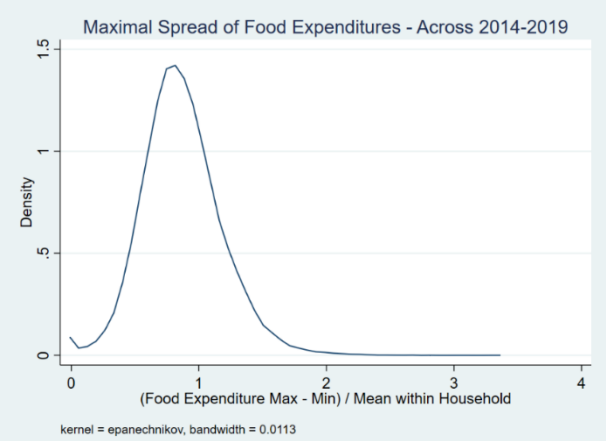


b. Ultra-processed foods (snacks)

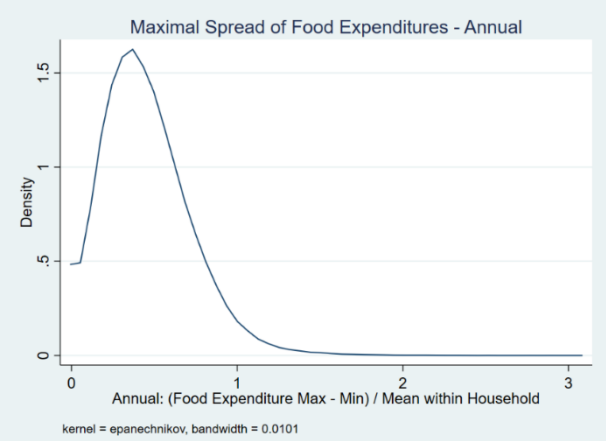


Note: The graphs above depict monthly per capita expenditures, share of food budgets and percentage of households that report non-zero expenditures on paid meals, ultra-processed foods, fruits and vegetables from April 2014-March 2020. Expenditure values are expressed in real terms (2014 prices) , by adjusting for inflation using Consumer Price Index (Central Statistical Office, India). The decline in most values in March 2020 may be due to the Coronavirus lockdown implemented on 22nd March, 2020 by Government of India. The horizontal blue lines represent rural populations and red lines represent urban populations in the graphs. The vertical red solid line marks November, 2016 when demonetization was announced nationally and the red dotted line marks July 2017 when the Goods and Services Tax was implemented nationally. Paid Meals or eating out includes expenditure on food in restaurants, cafes, canteens and street vendor shops. Ultra-processed foods or snacking includes biscuits, noodles, flakes, mithai, ready to eat, dry fruits, chocolates, cakes, soft drinks.

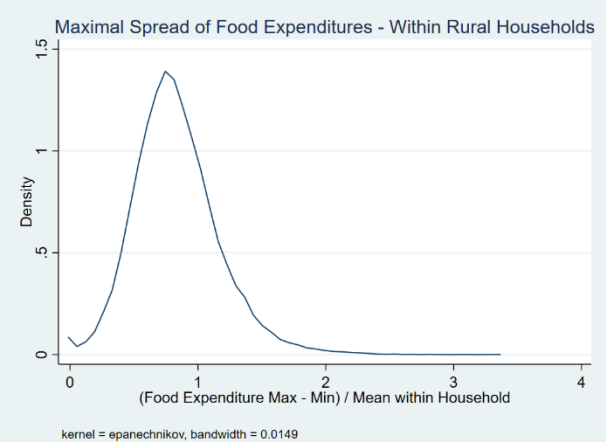
Figure 4: Food Expenditure variability within households



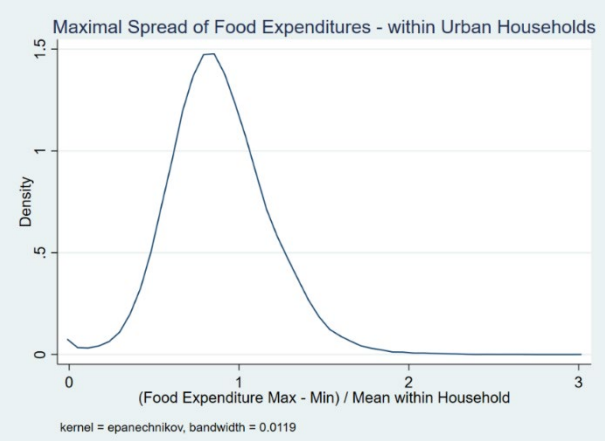
A. Overall Spread



B. Annual Spread



C. Rural Spread

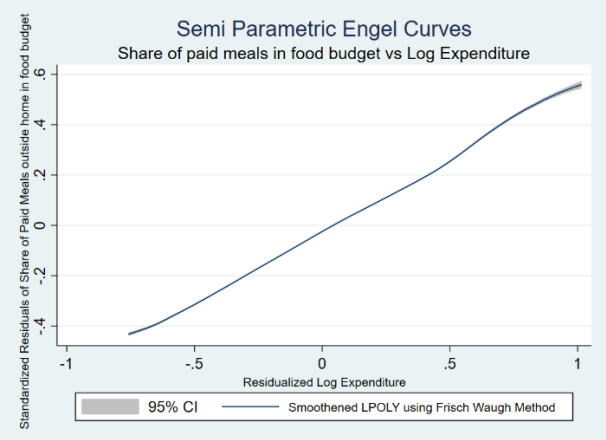


D. Urban Spread

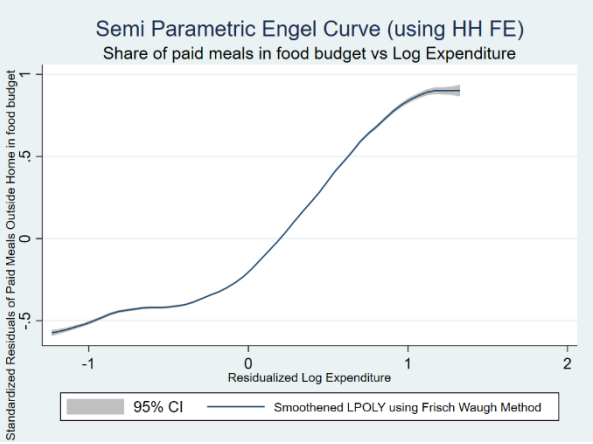
Note: The graphs above depict the variability in food expenditure within households. Figure A presents the spread for the entire sample across 2014-2019. Figure B presents the spread calculated annually. Figure C and D present the spreads by region, that is for rural and urban households respectively.

Figure 5: Semi Parametric Engel Curves using Frisch Waugh Method

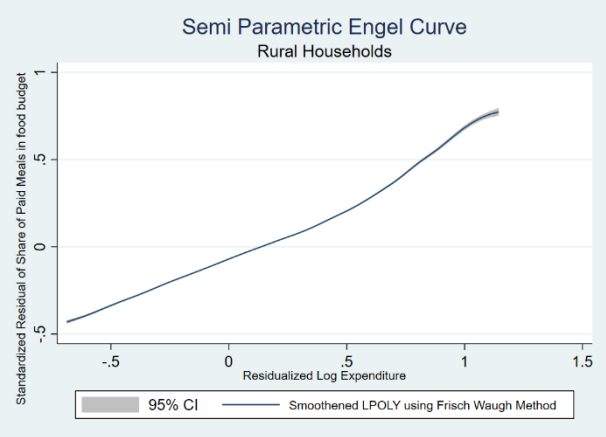
5.1. Share of Paid Meals Outside Home in food budget vs Log Expenditure



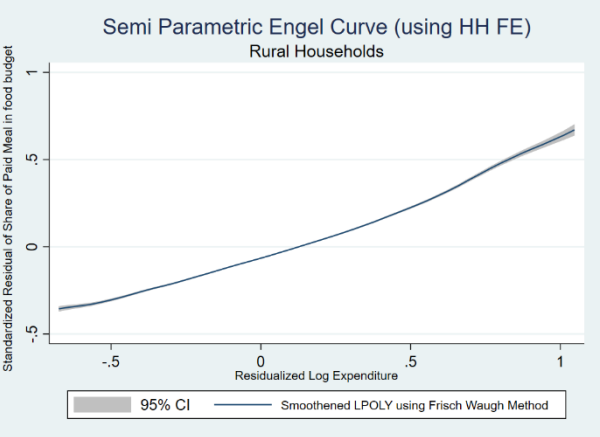
A. Full Sample: Cross HH



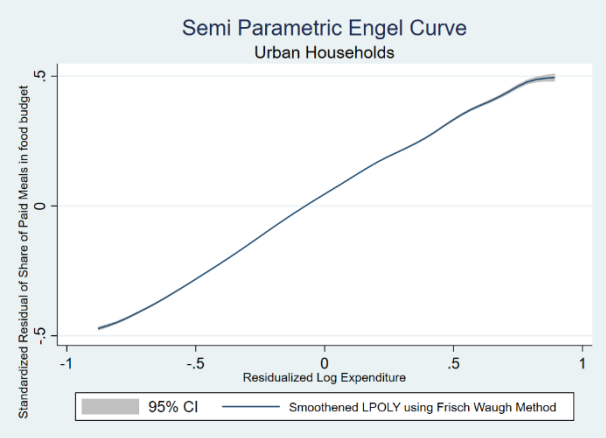
B. Full Sample: Within HH



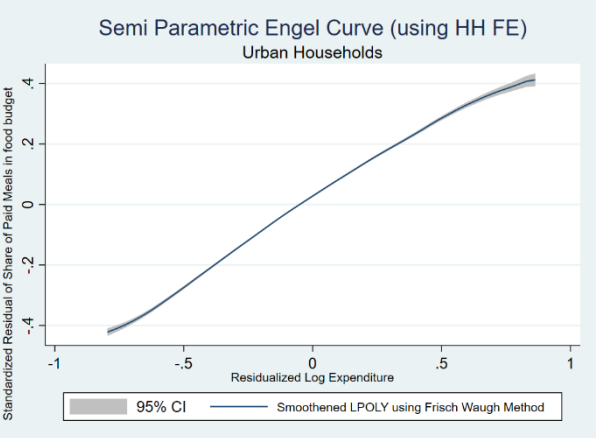
C. Rural Sample: Cross HH



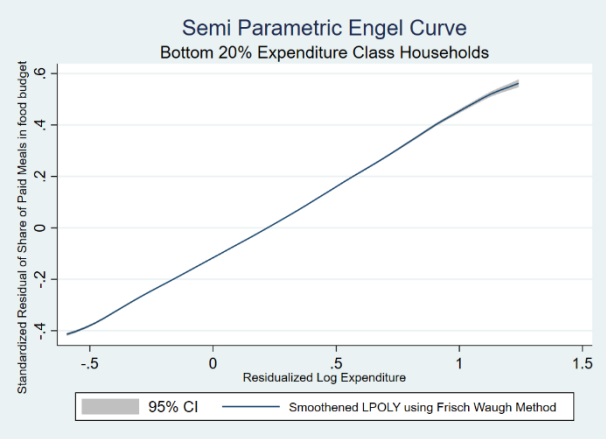
D. Rural Sample: Within HH



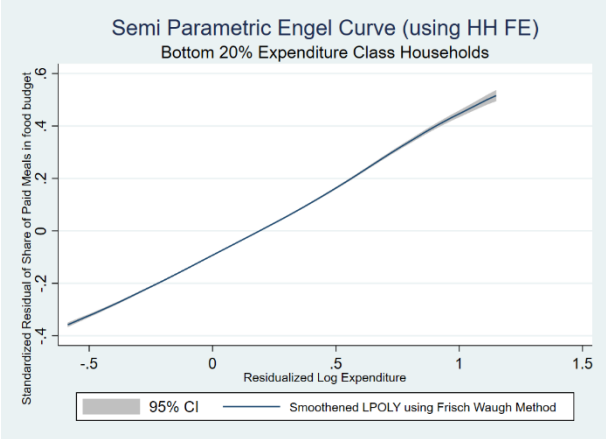
E. Urban Sample: Cross HH



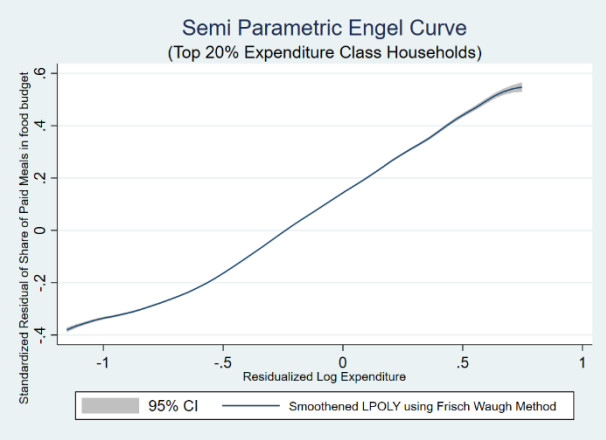
F. Urban Sample: Within HH



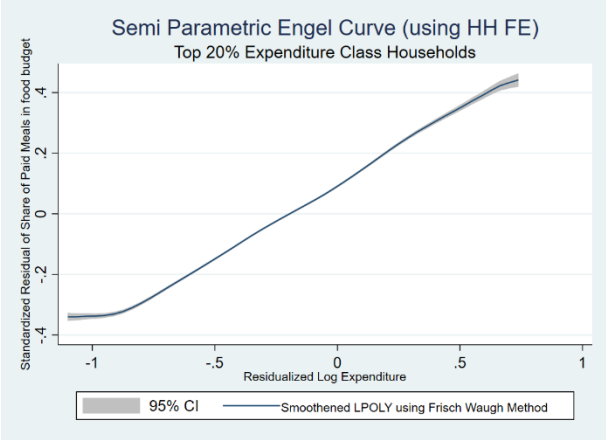
G. Poor Sample: Cross HH



H. Poor Sample: Within HH



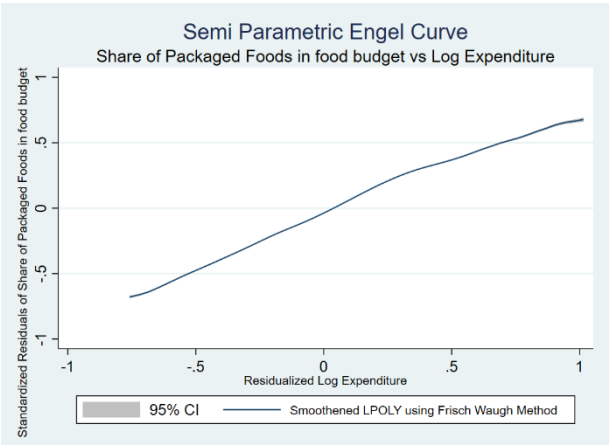
I. Wealthy Sample: Cross HH



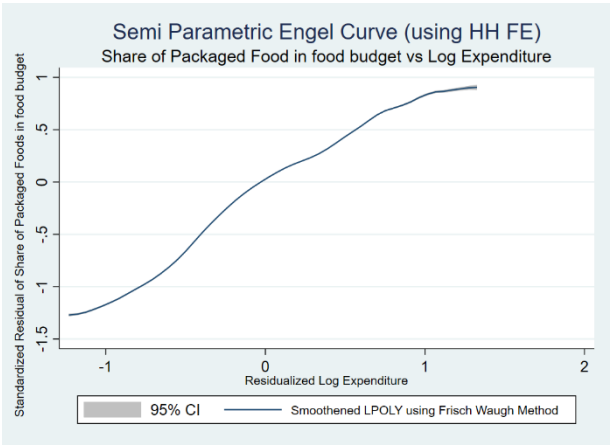
J. Wealthy Sample: Within HH

Note: The graphs above depict non-parametric estimates of food budget shares on paid meals vs log of total expenditure. The left-hand column (cross HH) analysis controls for household demographic variables like log household size, number of adult men and women, young girls and boys, elder men and women, number of earning members and whether the household has an earning woman member and domestic help. It also includes region by survey round fixed effects to account for and local price variations. The right-hand column (within HH) analysis includes household fixed effects to account for unobserved household variation and log of household size. The Frisch-Waugh Method is used to residualize budget shares and log expenditure on all other explanatory variables and the plot is generated using a local polynomial smoothing function. The top and bottom 1% of residualized log expenditure values are trimmed. The residualized budget shares are standardized around their sample mean.

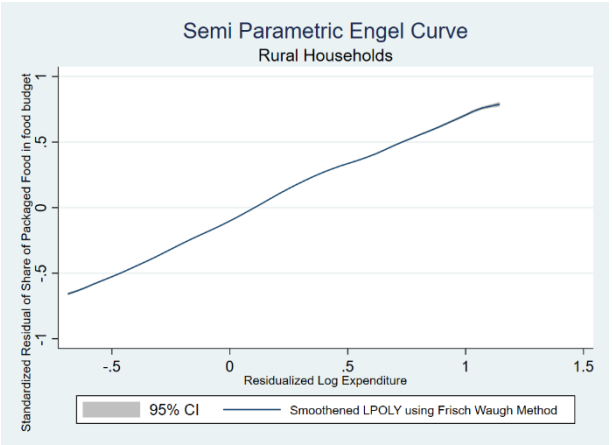
Figure 5.2. Share of Ultra-processed Foods in food budget vs Log Expenditure



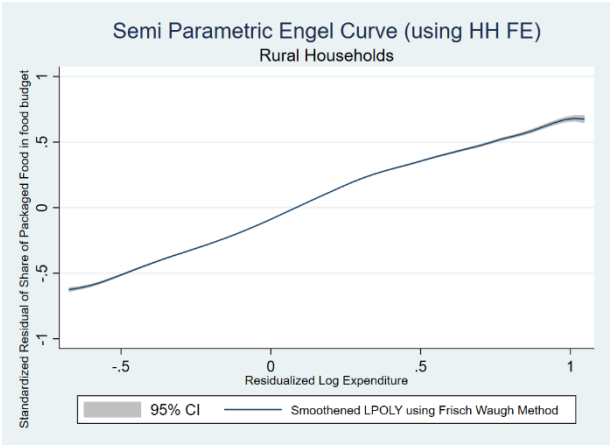
A. Full Sample: Cross HH



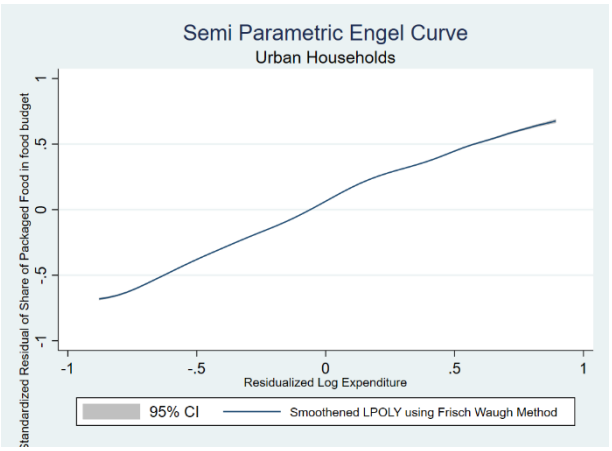
B. Full Sample: Within HH



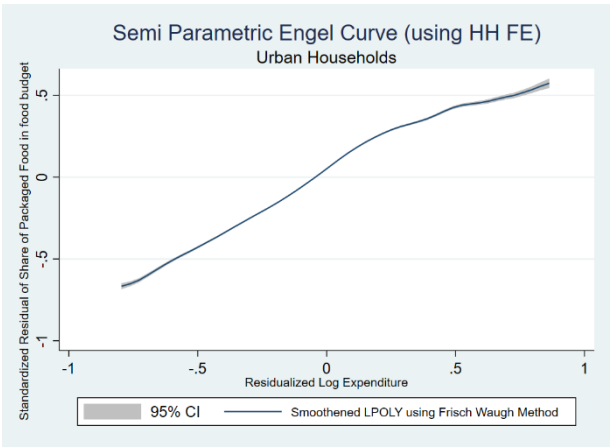
C. Rural Sample: Cross HH



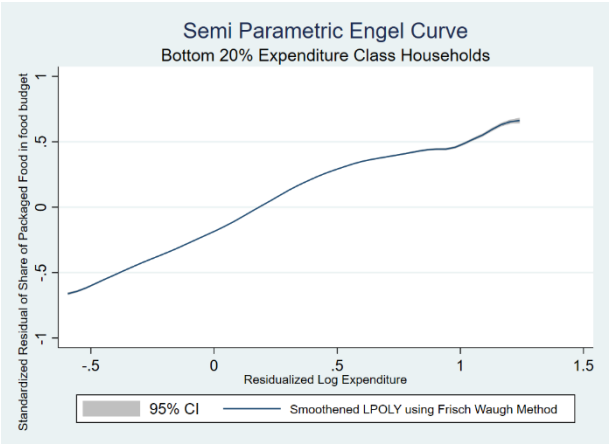
D. Rural Sample: Within HH



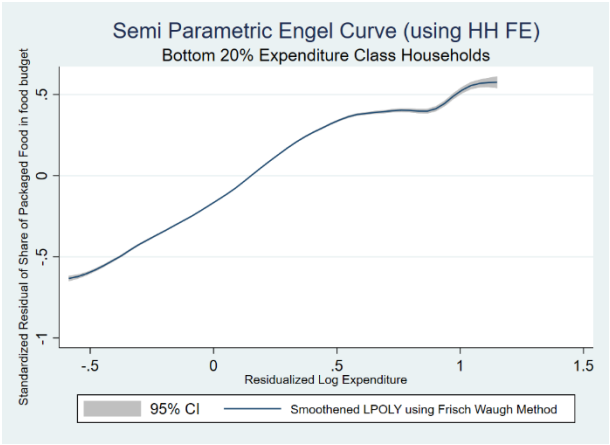
E. Urban Sample: Cross HH



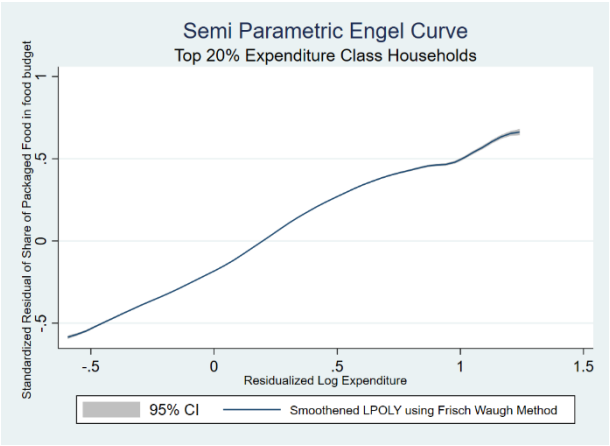
F. Urban Sample: Within HH



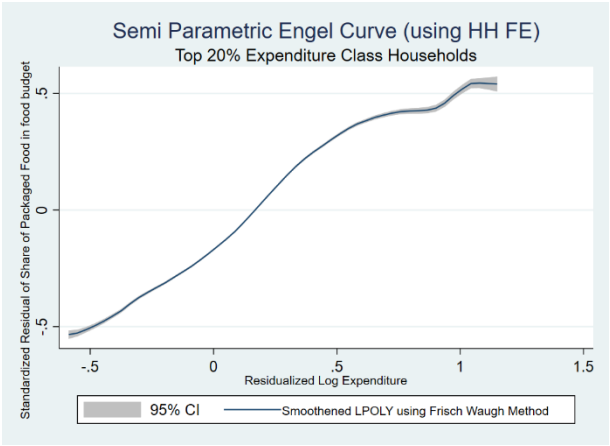
G. Poor Sample: Cross HH



H. Poor Sample: Within HH



I. Wealthy Sample: Cross HH



J. Wealthy Sample: Within HH

Note: The graphs above depict non-parametric estimates of food budget shares on ultra-processed foods vs log of total expenditure. The left-hand column (cross HH) analysis controls household demographic variables like log household size, number of adult men and women, young girls and boys, elder men and women, number of earning members and whether the household has an earning woman member and domestic help. It also includes region by survey round fixed effects to account for and local price variations. The right-hand column (within HH) analysis controls household fixed effects to account for unobserved household variation and log of household size. The Frisch-Waugh Method is used to residualize budget shares and log expenditure on all other explanatory variables and the plot is generated using a local polynomial smoothing function. The top and bottom 1% of residualized log expenditure values are trimmed. The residualized budget shares are standardized around their sample mean.

Appendix

Table A.1 Summary Statistics for Panel Data Sample

2017-2019	*Full Sample*		*Urban Sample*		*Rural Sample*	
Variables	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Household Size	4.10	1.65	3.93	1.60	4.21	1.67
Monthly Consumption Expenditure	12071.31	8538.67	13820.15	8077.71	10930.81	8637.64
Monthly Income	19468.73	23120.34	24370.70	24138.07	16271.92	21847.06
Monthly Food Expenditure (Rs.)	5749.47	4657.60	6216.21	2487.10	5445.08	5618.88
Share of food in total expenditure (%)	51%	12%	49%	12%	53%	12%
Households report paid meal expenses	68%	47%	71%	45%	66%	47%
Share of paid meal in food expenses (%)	4%	4%	4%	4%	3%	3%
Monthly paid meal expenses (Rs.)	231.01	295.29	297.65	372.35	187.55	221.03
Households report ultra-processed food expenses	97%	18%	97%	18%	97%	18%
Share of ultra-processed food in food expenses (%)	10%	6%	10%	6%	9%	6%
Monthly ultra-processed food expenses (Rs.)	605.25	4043.75	703.86	601.44	540.94	5173.91
Households report vegetable expenses	100%	4%	100%	4%	100%	4%
Share of vegetables in food expenses (%)	16%	6%	16%	6%	17%	6%
Monthly vegetable expenses (Rs.)	645.68	407.31	693.03	427.76	614.80	390.32
Households report fruit expenses	82%	38%	87%	34%	79%	41%
Share of fruits in food expenses (%)	3%	2%	3%	2%	3%	2%
Monthly fruit expenses (Rs.)	185.15	178.95	214.13	184.55	166.25	172.59
Number of women members	1.93	1.05	1.87	1.01	1.97	1.07
Household has at least one child (0-15 years)	48%	50%	43%	50%	50%	50%
Household has at least one elder (>60 years)	22%	42%	23%	42%	22%	41%
Marital Status of Household Head (Married)	93%	25%	92%	27%	94%	24%
Number of earning members	1.33	0.73	1.26	0.71	1.38	0.73
At least one earning woman in multi-earner HH	10%	30%	8%	28%	11%	31%
Household Religion Group						
Hindu	86%	34%	85%	36%	87%	33%
Muslim	9%	29%	10%	29%	9%	29%
Household Caste Group						
General Caste	31%	46%	37%	48%	27%	44%
Other Backward Classes	39%	49%	39%	49%	39%	49%
Scheduled Caste	25%	43%	21%	41%	27%	45%
Scheduled Tribe	5%	21%	3%	16%	6%	24%
Education Group of majority members in Household						
Graduates	19%	39%	28%	45%	13%	33%
Matriculates	34%	47%	36%	48%	33%	47%
Literate	44%	50%	34%	47%	51%	50%

2017-2019	*Full Sample*		*Urban Sample*		*Rural Sample*	
Illiterate	3%	18%	2%	14%	4%	20%
Occupation Group of majority members in Household						
Entrepreneurial Class	17%	38%	28%	45%	11%	31%
Salaried Class	21%	41%	34%	47%	13%	34%
Farmer Class	23%	42%	3%	17%	37%	48%
Daily Wage-Earning Class	28%	45%	22%	42%	32%	47%
Business + Salaried Class	2%	13%	3%	17%	1%	10%
Household Wealth Index Group (PCA) [1 being lowest]						
1	16%	37%	18%	39%	15%	35%
2	20%	40%	20%	40%	21%	40%
3	21%	40%	21%	40%	21%	40%
4	21%	41%	21%	41%	21%	40%
5	22%	42%	20%	40%	24%	42%
Household spends on domestic help	9%	29%	16%	37%	5%	21%
Household spends on remittance	1%	9%	1%	10%	1%	9%
Household spends on fitness	1%	8%	1%	11%	0%	5%
Household spends on cooking fuel	80%	40%	79%	41%	84%	36%
Regional Zone Group						
Central	6%	24%	8%	26%	6%	23%
East	26%	44%	15%	36%	32%	47%
South	20%	40%	26%	44%	16%	36%
West	19%	39%	24%	43%	15%	36%
North	30%	46%	27%	44%	31%	46%
City Size Group						
Village	61%	49%			100%	0%
Small <20,000 households	15%	36%	39%	49%		
Medium (20,000-60,000 households)	7%	25%	17%	37%		
Large (60,000-200,000 households)	6%	24%	15%	36%		
Very Large (>200,000 households)	11%	32%	29%	45%		
N	38424		28490		9934	

Note: All values in the table above are weighted using CMIE All-India weights. Paid Meals include meals at restaurants, cafes, canteens, or street vendors. Ultra-processed foods include biscuits, salty snacks or "namkeen", noodles, pasta and flakes, ready-to-eat foods (semi-prepared with preservatives), "mithai" or Indian sweets, dry fruits, chocolates, cakes, ice creams, aerated beverages, and canned juices that are either fried in oil and/or high in salt or sugar content. The Wealth Index Group is assigned based on wealth rank calculated using Principal Component Analysis. The regional zones are assigned based on geographical location of states-Central (Chhattisgarh and Madhya Pradesh), East (Assam, Bihar, Jharkhand, Odisha and West Bengal), South (Andhra Pradesh, Karnataka, Kerala, Puducherry, Tamil Nadu and Telangana) and North (Delhi, Chandigarh, Haryana, Himachal Pradesh, Jammu & Kashmir, Punjab, Uttar Pradesh and Uttarakhand). The numbers are similar and comparable to the summary statistics presented in Table 1 for the entire sample.

Table A.2: Income Elasticities using Share of Food Budget (Working Leser Model)

A.2.1 Cross Sectional Data (2017-2019)

A. Share of Paid Meals in Food Budget	(1) Full Sample	(2) Rural Sample	(3) Urban Sample	(4) p20 Sample	(5) p80 Sample
Average Share of Paid Meals in Food Budget	.0382262	.0348344	.0450349	.031949	.0519129
Calculated Income Elasticity	1.04	1.01	1.16	1.02	1.07
Log Monthly Household Income	0.00171***	0.000300***	0.00734***	0.000684***	0.00342***
	(0.000261)	(5.88e-05)	(0.000992)	(0.000113)	(0.000437)
Log Household Size	-0.00208***	-0.00122***	-0.00430***	-0.00186***	0.00194
	(0.000449)	(0.000446)	(0.00103)	(0.000629)	(0.00121)
Number of boys in HH (0-15 years)	-0.000983***	-0.000506***	-0.00113***	-9.19e-05	-0.00203***
	(0.000155)	(0.000130)	(0.000343)	(0.000153)	(0.000493)
Number of girls in HH (0-15 years)	-0.000962***	-0.000660***	-0.000851***	-0.000187	-0.00210***
	(0.000141)	(0.000127)	(0.000310)	(0.000139)	(0.000520)
Number of adult women in HH (16-60 years)	-0.000394***	-0.000370***	-0.000752**	1.88e-06	-0.00127***
	(0.000122)	(0.000127)	(0.000302)	(0.000151)	(0.000475)
Number of adult men in HH (16-60 years)	5.30e-05	9.95e-05	-0.000500	0.000141	-0.000213
	(0.000142)	(0.000131)	(0.000382)	(0.000170)	(0.000508)
Number of elder men in HH (>60 years)	-0.000483*	-0.000559**	-0.000672	2.29e-05	-0.00108
	(0.000252)	(0.000231)	(0.000556)	(0.000272)	(0.000794)
Number of elder women in HH (>60 years)	-0.000556*	-0.000602**	-0.000903*	0.000163	-0.00339***
	(0.000300)	(0.000251)	(0.000499)	(0.000290)	(0.000638)
Household has domestic help	0.0176***	0.0110***	0.0137***	0.00952***	0.0159***
	(0.00207)	(0.000738)	(0.00165)	(0.00112)	(0.00162)
Household has an earning woman member	-0.00129*	0.000383	-7.76e-06	-0.000846**	-0.00256**
	(0.000712)	(0.000372)	(0.000724)	(0.000397)	(0.00129)
Number of earning members in HH	-0.000702***	0.000142	-0.000712**	-8.49e-05	-2.93e-05
	(0.000169)	(0.000158)	(0.000350)	(0.000196)	(0.000596)
State * Survey Round FE	Yes	Yes	Yes	Yes	Yes
Household FE	No	No	No	No	No

Number of unique households	177296	63613	113683	42678	30167
Observations	4,617,628	1,564,419	3,053,209	1,154,728	750,770
R-squared	0.231	0.278	0.210	0.223	0.230

Robust standard errors in parentheses clustered at PSU level

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

Note: The regression coefficients presented in the table above are from cross-sectional regressions. The outcome variable is the share of paid meals outside home in food budget while the main variable of interest on the RHS is log of household monthly income. Using average share values and regression coefficients we calculate the income elasticity of share of paid meals outside home in food budget. Columns 1 denotes results for the whole sample, while Columns 2 and 3 denote results for rural and urban subsamples respectively. Columns 4 and 5 denote results for the households belonging to the bottom and top quintile expenditure classes respectively, that is, the bottom 20% and top 20% expenditure group households. All regressions are based on the Working-Leser Model where the dependent variable is the share of food budget spent on paid meals. In each regression we control for state into survey round fixed effects to account for price variations across space and time. We also control for log of household size to get per capita elasticities effectively and for other household composition and employment variables such as – number of young girls and boys, adult women and men, and elderly women and men in the household, whether the household has an earning woman member, whether the household has domestic help and the total number of earning members in the family. Elasticities calculated using the following formula: 1 + (beta_coefficient [Log_income] / Average share of paid meals expense in food budget)

B. Share of Ultra-processed Foods in Food Budget	(1)	(2)	(3)	(4)	(5)
	Full Sample	Rural Sample	Urban Sample	p20 Sample	p80 Sample
Average Share of Ultra-processed Foods in Food Budget	.0950663	.0912135	.1028003	.0904385	.1044429
Calculated Income Elasticity	1.03	1.01	1.10	1.02	1.05
Log Monthly Household Income	0.00281***	0.000925***	0.0106***	0.00152***	0.00476***
	(0.000230)	(0.000104)	(0.000941)	(0.000175)	(0.000395)
Log Household Size	0.0119***	0.0122***	0.0101***	0.00481***	0.0104***
	(0.000757)	(0.000776)	(0.00132)	(0.000983)	(0.00168)
Number of boys in HH (0-15 years)	-9.74e-05	0.000163	0.00103**	0.00106***	0.00549***
	(0.000237)	(0.000254)	(0.000515)	(0.000285)	(0.000799)
Number of girls in HH (0-15 years)	-0.000586**	-0.000555**	0.000994*	0.000798***	0.00489***
	(0.000232)	(0.000248)	(0.000513)	(0.000270)	(0.000783)
Number of adult women in HH (16-60 years)	-0.00117***	-0.00142***	-0.00121***	6.00e-05	0.00154***
	(0.000218)	(0.000244)	(0.000377)	(0.000291)	(0.000568)
Number of adult men in HH (16-60 years)	-0.00152***	-0.00138***	-0.00231***	-0.000842***	0.00225***
	(0.000221)	(0.000252)	(0.000401)	(0.000310)	(0.000557)
Number of elder men in HH (>60 years)	-0.00637***	-0.00599***	-0.00711***	-0.00204***	-0.00558***
	(0.000399)	(0.000415)	(0.000692)	(0.000506)	(0.000802)
Number of elder women in HH (>60 years)	-0.00323***	-0.00346***	-0.00342***	-0.00176***	-0.00229***
	(0.000359)	(0.000411)	(0.000612)	(0.000507)	(0.000855)
Household has domestic help	0.0226***	0.0161***	0.0157***	0.0131***	0.0227***
	(0.00222)	(0.00121)	(0.00283)	(0.00181)	(0.00187)
Household has an earning woman member	-0.000541	0.00126**	0.00103	-0.00271***	0.00287**
	(0.000851)	(0.000592)	(0.00105)	(0.000732)	(0.00135)
Number of earning members in HH	-0.00372***	-0.00212***	-0.00487***	-0.00209***	-0.00402***
	(0.000275)	(0.000290)	(0.000451)	(0.000344)	(0.000722)
State * Survey Round FE	Yes	Yes	Yes	Yes	Yes
Household FE	No	No	No	No	No
Number of unique households	177296	63613	113683	42678	30167
Observations	4,617,628	1,564,419	3,053,209	1,154,728	750,770
R-squared	0.220	0.216	0.256	0.220	0.308

Robust standard errors in parentheses clustered at PSU level
*** p<0.01, ** p<0.05, * p<0.1

Note: The regression coefficients presented in the table above are from cross-sectional regressions. The outcome variable is the share of ultra-processed food in food budget while the main variable of interest on the RHS is log of household monthly income. Using average share values and regression coefficients we calculate the income elasticity of share of ultra-processed food in food budget. Columns 1 denotes results for the whole sample, while Columns 2 and 3 denote results for rural and urban subsamples respectively. Columns 4 and 5 denote results for the households belonging to the

bottom and top quintile expenditure classes respectively, that is, the bottom 20% and top 20% expenditure group households. All regressions are based on the Working-Leser Model where the dependent variable is the share of food budget spent on ultra-processed foods. In each regression we control for state into survey round fixed effects to account for price variations across space and time. We also control for log of household size to get per capita elasticities effectively and for other household composition and employment variables such as – number of young girls and boys, adult women and men, and elderly women and men in the household, whether the household has an earning woman member, whether the household has domestic help and the total number of earning members in the family. Elasticities calculated using the following formula: 1 + (beta_coefficient [Log_income] / Average share of ultra-processed food expense in food budget)

A.2.2 Panel Data (2017-2019)

A. Share of Paid Meals in Food Budget	(1) Full Sample	(2) Rural Sample	(3) Urban Sample	(4) p20 Sample	(5) p80 Sample
Average Share of Paid Meals in Food Budget	.0371511	.0331568	.0431516	.0319325	.0506925
Calculated Income Elasticity	1.00	0.99	1.05	1.00	1.01
Log Monthly Household Income	1.16e-05 (9.12e-05)	-0.000231*** (8.10e-05)	0.00232*** (0.000431)	-5.04e-05 (0.000117)	0.000472* (0.000250)
Log Household Size	-0.00160** (0.000774)	-0.00112 (0.000950)	-0.00338*** (0.00124)	-0.00138 (0.00103)	-0.00323 (0.00201)
State * Survey Round FE	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes
Number of unique households	32,708	8,223	24,485	9,277	4,600
Observations	1,177,488	296,028	881,460	333,972	165,600
R-squared	0.093	0.124	0.089	0.100	0.120

Robust standard errors in parentheses clustered at PSU level
*** p<0.01, ** p<0.05, * p<0.1

Note: The regression coefficients presented in the table above are from panel regressions. The outcome variable is the share of paid meals outside home in food budget while the main variable of interest on the RHS is Log of household monthly income. Using average share values and regression coefficients we calculate the income elasticity of share of paid meals outside home in food budget. Columns 1 denotes results for the whole sample, while Columns 2 and 3 denote results for rural and urban subsamples respectively. Columns 4 and 5 denote results for the households belonging to the bottom and top quintile expenditure classes respectively, that is, the bottom 20% and top 20% expenditure group households. All regressions are based on the Working-Leser Model where the dependent variable is the share of food budget spent on ultra-processed foods. In each regression we control for household fixed effects and state into survey round fixed effects to account for unobserved household heterogeneity and price variations across space and time. We also control for log of household size to get per capita elasticities effectively. Elasticities calculated using the following formula: 1 + (beta_coefficient [Log_income] / Average share of paid meals expense in food budget)

B. Share of Ultra-processed Foods in Food Budget	(1)	(2)	(3)	(4)	(5)
	Full Sample	Rural Sample	Urban Sample	p20 Sample	p80 Sample
Average Share of Ultra-processed Foods in Food Budget	.0973774	.0927578	.1043169	.093332	.1086543
Calculated Income Elasticity	1.00	1.00	1.02	1.00	1.01
Log Monthly Household Income	0.000253	5.16e-05	0.00236***	0.000119	0.00116***
	(0.000159)	(0.000166)	(0.000511)	(0.000246)	(0.000354)
Log Household Size	0.00962***	0.00956***	0.00969***	0.00482***	0.0138***
	(0.00119)	(0.00155)	(0.00179)	(0.00163)	(0.00279)
State * Survey Round FE	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes
Number of unique households	32,708	8,223	24,485	9,277	4,600
Observations	1,177,488	296,028	881,460	333,972	165,600
R-squared	0.111	0.136	0.095	0.166	0.090

Robust standard errors in parentheses clustered at PSU level

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

Note: The regression coefficients presented in the table above are from panel regressions. The outcome variable is the share of ultra-processed foods in food budget while the main variable of interest on the RHS is Log of household monthly income. Using average share values and regression coefficients we calculate the income elasticity of share of ultra-processed foods in food budget. Columns 1 denotes results for the whole sample, while Columns 2 and 3 denote results for rural and urban subsamples respectively. Columns 4 and 5 denote results for the households belonging to the bottom and top quintile expenditure classes respectively, that is, the bottom 20% and top 20% expenditure group households. All regressions are based on the Working-Leser Model where the dependent variable is the share of food budget spent on ultra-processed foods. In each regression we control for household fixed effects and state into survey round fixed effects to account for unobserved household heterogeneity and price variations across space and time. We also control for log of household size to get per capita elasticities effectively. Elasticities calculated using the following formula: 1 + (beta_coefficient [Log_income] / Average share of ultra-processed food expense in food budget)

Table A.3: Linear Probability Regression on determinants of spending on paid meals outside home

Linear Probability Model	(1) Spends on Ultra-processed Food (Y/N)
Log Expenditure	0.0561***
	(0.00410)
Log Household size	0.00382*
	(0.00208)
Number of women in Household	-0.00146***
	(0.000330)
HH has at least one child (<=15 years)	0.0103***
	(0.000945)
HH has at least one elder member (>=60 years)	-0.00768***
	(0.000961)
HH head is married	-0.00431**
	(0.00219)
HH has an earning woman	0.00914***
	(0.00207)
Number of earning members in HH	-0.00262***
	(0.000525)
Religious Group (Base= Hindi)	
Muslim	-0.000313
	(0.00232)
Others	-0.00473*
	(0.00270)
Caste Category (Base=General)	
OBC	0.00239*
	(0.00131)
SC	0.00466***
	(0.00176)
ST	-0.00802***
	(0.00306)
Educational qualifications of majority members in HH (Base= Graduates)	
Matriculates	0.00309***
	(0.000871)
Literate	0.00201*
	(0.00116)
Illiterate	-0.00101
	(0.00357)
Occupation class of majority members in HH (Base=Entrepreneurial class)	
salaried class	0.000367
	(0.00187)
farmer class	-0.00371**
	(0.00147)
daily wage earner	-0.00186
	(0.00153)
Business + salaried	-0.00301
	(0.00200)

Linear Probability Model	(1) Spends on Ultra-processed Food (Y/N)
Others	-0.00530**
	(0.00253)
Wealth Index Rank (PCA) [Base=1]	
Rank 2	-0.000568
	(0.00124)
Rank 3	-0.00390**
	(0.00172)
Rank 4	-0.00391**
	(0.00173)
Rank 5	-0.0101***
	(0.00214)
HH spends on domestic help	0.0108
	(0.00762)
HH has remittance expenses	-0.0293***
	(0.0113)
HH spends on fitness	-0.0157**
	(0.00611)
HH spends on cooking fuel	-0.00759***
	(0.00161)
Regional Zone [Base=Central]	
East	0.0179***
	(0.00285)
South	-0.0854***
	(0.0134)
West	-0.0404***
	(0.00518)
North	-0.00988**
	(0.00467)
City Size [Base= Village]	
Small (<20,000 households)	-0.00487
	(0.00630)
Medium (20,000-60,000 households)	-0.00566
	(0.00414)
Large (60,000-200,000 households)	-0.000519
	(0.00497)
Very Large (>200,000 households)	0.000494
	(0.00618)
Survey Round (Wave) [Base=Jan-April 2017]	
May-August, 2017	0.0188***
	(0.00287)
September-December, 2017	0.0342***
	(0.00435)
Jan-April, 2018	0.0465***
	(0.00426)
May-August, 2018	0.0499***
	(0.00430)
September-December, 2018	0.0344***
	(0.00459)
Jan-April, 2019	0.0307***

Linear Probability Model	(1) Spends on Ultra-processed Food (Y/N)
	(0.00541)
May-August, 2019	0.0349***
	(0.00446)
September-December, 2019	0.0309***
	(0.00463)
State FE	Yes
Observations	4,617,628
R-squared	0.076

Robust standard errors in parentheses clustered at PSU level
*** p<0.01, ** p<0.05, * p<0.1

Note: The results presented above are from a linear probability model that analyses the determinants of the likelihood that a family spends money on ultra-processed foods (Column 1). The outcome variables are binary and take on a value of 1 if a household had a non-zero expense on ultra-processed foods. The explanatory variables include: log of total household monthly expenditure, log of household size, number of women in the household, binary variables for whether the household has a child (member <15 years), whether the household has an elder (member >60 years), whether the household head is married, and whether the household has an earning woman member. It also examines other demographic characteristics such as: number of earning members in the household, the religious and caste group the household, education qualifications of majority members in the household, occupation classification of majority members in the household, the wealth index rank (measured using Principal Component Analysis on the assets and amenities a household owns), the likelihood of a household having domestic help, spending on cooking fuel, sending remittance home and spending on fitness. Lastly, we control for geographical location of the household and include Regional and survey round fixed effects.

Table A.4: Expenditure Elasticity for paid meal and ultra-processed food expenses

I. Cross-Sectional Data

A. Expenditure on Paid Meals Outside Home (Rs.)	(1)	(2)	(3)	(4)	(5)
	Full Sample	Rural Sample	Urban Sample	p20 Sample	p80 Sample
Average Expenditure on Paid Meals Outside Home (Rs.)	230.2879	193.7004	303.7324	170.7899	361.1853
Calculated Elasticity	2.09	1.94	2.07	2.15	1.88
Log Monthly Household Expenditure	251.0***	182.2***	324.2***	196.2***	317.9***
	(15.70)	(3.424)	(27.00)	(4.228)	(24.93)
Log Household Size	-33.76***	-16.37***	-41.63***	-31.45***	-33.98***
	(5.286)	(2.570)	(8.301)	(3.225)	(8.396)
Number of boys in HH (0-15 years)	-4.323***	-1.368*	-9.956***	0.381	-14.07***
	(1.003)	(0.759)	(2.832)	(0.830)	(3.888)
Number of girls in HH (0-15 years)	-3.154***	-1.579**	-7.115***	0.301	-13.47***
	(0.858)	(0.760)	(2.528)	(0.789)	(4.154)
Number of adult women in HH (16-60 years)	-3.778***	-2.794***	-6.680***	-2.030**	-4.671
	(0.872)	(0.784)	(2.547)	(0.880)	(4.188)
Number of adult men in HH (16-60 years)	-5.238***	-2.768***	-9.673***	-2.317**	-10.38**
	(1.205)	(0.785)	(3.190)	(1.071)	(4.315)
Number of elder men in HH (>60 years)	-4.486**	-3.179**	-5.107	-1.750	-12.52*
	(1.998)	(1.500)	(4.549)	(1.487)	(7.146)
Number of elder women in HH (>60 years)	-1.359	-0.323	-3.237	-0.974	-9.594*
	(2.181)	(1.627)	(3.853)	(1.603)	(5.180)
Household has domestic help	92.23***	48.34***	71.76***	40.24***	83.85***
	(16.31)	(4.220)	(14.32)	(7.489)	(13.34)
Household has an earning woman member	-10.86**	1.348	-5.827	-2.823	-29.75***
	(5.286)	(2.287)	(4.948)	(2.098)	(10.88)
Number of earning members in HH	2.862***	4.081***	12.58***	2.825***	10.88**
	(1.088)	(0.958)	(3.522)	(1.083)	(5.097)
	(5,993)	(29.22)	(246.7)	(36.24)	(236.1)
State * Survey Rounds FE	Yes	Yes	Yes	Yes	Yes
Number of households	177296	63613	113683	42678	30167
Observations	4,617,628	1,564,419	3,053,209	1,154,728	750,770
R-squared	0.343	0.373	0.327	0.306	0.347

Robust standard errors in parentheses clustered at PSU level

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

Note: The regression coefficients presented in the table above are from cross-sectional regressions. The outcome variable is the actual expenditure on paid meals outside home while the main variable of interest on the RHS is log of household monthly expenditure. Using average share values and regression coefficients we calculate the expenditure elasticity of share of paid meals outside home in food budget. Columns 1 denotes results for the whole sample, while Columns 2 and 3 denote results for rural and urban subsamples respectively. Columns 4 and 5 denote results for the households belonging to the bottom and top quintile expenditure classes respectively, that is, the bottom 20% and top 20% expenditure group households. All regressions are based on the Working-Leser Model results where the dependent variable is the monthly amount spent on paid meals outside home. In each regression we control for state into survey round fixed effects to account for price variations across space and time. We also control for log of household size to get per capita elasticities effectively and for other household composition and employment variables such as – number of young girls and boys, adult women and men, and elderly women and men in the household, whether the household has an earning woman member, whether the household has domestic help and the total number of earning members in the family. Elasticities calculated using the following formula: 1 + (beta_coefficient [Log_exp] / Average paid meal expense)

B. Expenditure on Ultra-processed Food (Rs.)	(1)	(2)	(3)	(4)	(5)
	Full Sample	Rural Sample	Urban Sample	p20 Sample	p80 Sample
Average Expenditure on Ultra-processed Food (Rs.)	570.6167	512.4177	687.4435	491.4093	725.6165
Calculated Elasticity	2.03	1.99	1.99	2.11	1.85
Log Monthly Household Expenditure	586.7***	505.3***	677.9***	546.3***	614.5***
	(13.61)	(6.363)	(22.78)	(8.735)	(20.98)
Log Household Size	-32.22***	-21.61***	-34.20***	-62.05***	-74.32***
	(6.109)	(5.257)	(10.99)	(5.790)	(12.67)
Number of boys in HH (0-15 years)	14.86***	15.04***	22.28***	14.08***	54.93***
	(1.542)	(1.510)	(4.013)	(1.672)	(6.293)
Number of girls in HH (0-15 years)	14.76***	13.85***	23.07***	14.23***	56.71***
	(1.495)	(1.465)	(3.900)	(1.562)	(6.223)
Number of adult women in HH (16-60 years)	6.148***	3.876***	10.98***	4.227**	37.75***
	(1.388)	(1.496)	(3.151)	(1.768)	(5.038)
Number of adult men in HH (16-60 years)	-8.365***	-6.002***	-8.532**	-5.184***	18.71***
	(1.533)	(1.485)	(3.502)	(1.817)	(4.800)
Number of elder men in HH (>60 years)	-18.10***	-12.77***	-19.25***	-2.283	-18.78***
	(2.840)	(2.493)	(5.510)	(2.874)	(6.972)
Number of elder women in HH (>60 years)	-1.650	-0.567	0.658	-8.196***	22.44***
	(2.515)	(2.559)	(4.877)	(3.089)	(6.038)
Household has domestic help	94.33***	61.55***	59.84***	27.36*	130.8***
	(19.83)	(7.435)	(22.58)	(14.37)	(16.91)
Household has an earning woman member	-8.487	3.278	0.174	-10.51**	15.98
	(5.333)	(3.252)	(6.584)	(4.104)	(10.02)
Number of earning members in HH	-9.235***	-4.249**	-6.011*	-4.398**	-19.41***
	(1.726)	(1.696)	(3.383)	(1.935)	(5.776)
State * Survey Rounds FE	Yes	Yes	Yes	Yes	Yes
Number of households	177296	63613	113683	42678	30167
Observations	4,617,628	1,564,419	3,053,209	1,154,728	750,770
R-squared	0.473	0.438	0.506	0.451	0.522

Robust standard errors in parentheses clustered at PSU level

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

Note: The regression coefficients presented in the table above are from cross-sectional regressions. The outcome variable is the actual expenditure on ultra-processed food while the main variable of interest on the RHS is log of household monthly expenditure. Using average share values and regression coefficients we calculate the expenditure elasticity of share of paid meals outside home in food budget. Columns 1 denotes results for the whole sample, while Columns 2 and 3 denote results for rural and urban subsamples respectively. Columns 4 and 5 denote results for the households belonging to the bottom and top quintile expenditure classes respectively, that is, the bottom 20% and top 20% expenditure group households. All regressions are based on the Working-Leser Model results where the dependent variable is the monthly amount spent on ultra-processed food. In each regression we control for state into survey round fixed effects to account for price variations across space and time. We also control for log of household size to get per capita elasticities effectively and for other household composition and employment variables such as – number of young girls and boys, adult women and men, and elderly women and men in the household, whether the household has an earning woman member, whether the household has domestic help and the total number of earning members in the family.
Elasticities calculated using the following formula: 1 + (beta_coefficient [Log_exp] / Average ultra-processed food expense)

II. Panel Data

A. Expenditure on Paid Meals outside Home (Rs.)	(1)	(2)	(3)	(4)	(5)
	Full Sample	Rural Sample	Urban Sample	p20 Sample	p80 Sample
Average Expenditure on Paid Meals outside Home (Rs.)	224.4393	188.3598	278.6392	176.1517	346.533
Calculated Elasticity	1.89	1.86	1.91	2.10	1.68
Log Monthly Household Expenditure	200.3***	161.8***	252.5***	194.2***	237.2***
	(6.744)	(5.968)	(13.79)	(6.572)	(14.83)
Log Household Size	-14.19***	-7.026	-23.51***	-22.21***	-20.86
	(5.066)	(5.909)	(8.696)	(5.863)	(14.93)
Household FE	Yes	Yes	Yes	Yes	Yes
State * Survey Rounds FE	Yes	Yes	Yes	Yes	Yes
Number of households	32,708	8,223	24,485	9,277	4,600
Observations	1,177,488	296,028	881,460	333,972	165,600
R-squared	0.168	0.202	0.168	0.219	0.176

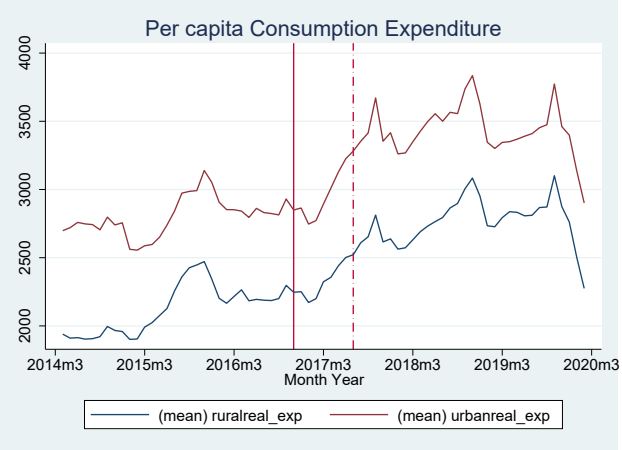
Robust standard errors in parentheses clustered at PSU level
*** p<0.01, ** p<0.05, * p<0.1

B. Expenditure on Ultra-processed Food (Rs.)	(1)	(2)	(3)	(4)	(5)
	Full Sample	Rural Sample	Urban Sample	p20 Sample	p80 Sample
Average Expenditure on Ultra-processed Food (Rs.)	584.9637	526.7827	672.3651	521.7113	733.858
Calculated Elasticity	1.34	1.31	1.38	1.37	1.32
Log Monthly Household Expenditure	200.3***	161.8***	252.5***	194.2***	237.2***
	(6.744)	(5.968)	(13.79)	(6.572)	(14.83)
Log Household Size	-14.19***	-7.026	-23.51***	-22.21***	-20.86
	(5.066)	(5.909)	(8.696)	(5.863)	(14.93)
Household FE	Yes	Yes	Yes	Yes	Yes
State * Survey Rounds FE	Yes	Yes	Yes	Yes	Yes
Number of households	1,177,488	296,028	881,460	333,972	165,600
Observations	0.168	0.202	0.168	0.219	0.176
R-squared	32,708	8,223	24,485	9,277	4,600

Robust standard errors in parentheses clustered at PSU level
*** p<0.01, ** p<0.05, * p<0.1

Note: The regression coefficients presented in the table above are from panel regressions. The outcome variable is the expenditure on paid meals and ultra-processed foods while the main variable of interest on the RHS is log of household monthly expenditure. Using average share values and regression coefficients we calculate the expenditure elasticity of paid meals and ultra-processed food expenses. Columns 1 denotes results for the whole sample, while Columns 2 and 3 denote results for rural and urban subsamples respectively. Columns 4 and 5 denote results for the households belonging to the bottom and top quintile expenditure classes respectively, that is, the bottom 20% and top 20% expenditure group households. All regressions are based on the Working-Leser Model results where the dependent variable is the share of food budget spent on ultra-processed foods. In each regression we control for household fixed effects and state into survey round fixed effects to account for unobserved household heterogeneity and price variations across space and time. We also control for log of household size to get per capita elasticities effectively. Elasticities calculated using the following formula: 1 + (beta_coefficient [Log_exp] / Average expense on paid meals/ ultra-processed foods.

Figure A.1: Trends in Monthly Per Capita Consumption Expenditure (MPCE) (Rs.)



Note: The graphs above depict monthly per capita expenditures trends from April 2014-March 2020. Expenditure values are expressed in real terms (2014 prices) , by adjusting for inflation using Consumer Price Index (Central Statistical Office, India). The decline in most values in March 2020 may be due to the Coronavirus lockdown implemented on 22nd March, 2020 by Government of India. The horizontal blue lines represent rural populations and red lines represent urban populations in the graphs. The vertical red solid line marks November, 2016 when demonetization was announced nationally and the red dotted line marks July 2017 when the Goods and Services Tax was implemented nationally.