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Processed foods, socio-economic status, and peri-urban obesity in India

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ABSTRACT

The ‘State of Food Security and Nutrition in the World 2020′ report states that switching to healthy diets will both prevent backsliding into hunger and help countries meet their sustainability goals. In 2019–2020, 17 percent of India’s adult population was undernourished. At the same time, however, 23 percent of all adults were obese. The increasing prevalence of obesity implies that improving diets and reducing risks for obesity and non-communicable diseases (NCDs) is a major food security challenge for India in the coming years. Overconsumption of calories from processed foods is known to increase the risk of obesity. To gain insights into the dietary transition and its relationship with obesity, we use cross-sectional data from a primary socio-economic survey conducted in the rural-urban interface of Bangalore, a mega-city in India that is characterized by high economic development. We show that for women in lower-middle socio-economic status (SES) groups, higher share of calories from semi-processed foods (SPF) is associated with a higher prevalence of obesity, while excess consumption of calories from ultra-processed foods (UPF) is associated with a higher obesity prevalence among women in higher SES groups. Older women and women who consume above the recommended daily allowance (RDA) of calories are more vulnerable to excess calories from SPF consumption than younger women and women who consume less than the RDA of calories. Furthermore, a lower prevalence of obesity is observed among women who consume excess calories from SPF but engage in labor-intensive occupational activity. These results speak to the need for interventions that incentivize weight loss and increased physical activity. The result that SPF consumption is associated with an increased prevalence of obesity especially among lower-middle SES group calls for interventions that increase access to and affordability of healthy diets. Policy instruments such as diversifying the public distribution system (PDS) are important to improve accessibility and affordability of healthy diets. In addition, increasing sugar and processed food taxes and incentivizing companies to invest in culturally sensitive food labeling should be considered to shift consumer demand towards healthier diet choices.

1. Introduction

The transition in food consumption patterns towards energy-dense, fatty, salty foods, and sweetened beverages is contributing to unhealthy diets and associated problems of overnutrition, especially in low- and middle-income countries (LMICs) (Popkin et al., 2012; Popkin and Ng, 2022; Reardon et al., 2021; Shetty, 2002). Transformations in the global food system from fresh markets to modern retail chains have increased the ease of access to processed and packaged foods and beverages (Demmler et al., 2018; Otterbach et al., 2021; Popkin, 2017; Yi et al., 2021). Furthermore, rising off-farm wages have increased the opportunity costs of preparing meals at home, leading to higher consumption of processed foods and more frequent dining out (Regmi and Dyck, 2001; Sauer et al., 2021).

Processed foods are the outcomes of different levels of industrial processing. Many industrial production processes make food highly palatable and less satiating, which encourages overconsumption (Fardet, 2016; Monteiro et al., 2013). Combined with reductions in physical activity in the course of structural transformation (ST),[1] excess calories from overconsumption lead to increased weight and prevalence of

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[1] Structural transformation (ST) leads to a reallocation of the workforce and economic output from labor-intensive (e.g. agriculture) to capital-intensive (e.g. industry and service) activities (Herrendorf et al., 2014). This reallocation reduces the physical energy expended in work (Monda et al., 2008). Along with these changes in work-effort in the labor force, ST is associated with greater urbanization and market access and, thus, greater dietary diversity (Rahman and Mishra, 2020). The latter is also associated with an increased access to processed foods and an increased prevalence of obesity (Popkin et al., 2012; Shetty, 2013).

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obesity in otherwise nutrition-insecure populations (Crimarco et al., 2021; Ford et al., 2017; Misra et al., 2011; Nardocci et al., 2021; Popkin et al., 2001; Popkin and Ng, 2022).

In India, the prevalence of obesity has increased rapidly in the last decade (NFHS-5, 2021; Nguyen et al., 2021). Aiyar et al. (2021b) show that this increase can be partly attributed to the spillover effect of ST from the nearby urban centers. Dang et al. (2019) find that the transition towards less physically demanding activities is correlated with obesity. Aiyar et al. (2021a) find that economic indicators and obesogenic factors are correlated with obesity among men, and biological and obesogenic factors are correlated with obesity among women. However, due to a lack of detailed dietary data, these authors acknowledge that they cannot explore the role of diets in the prevalence of obesity. Meenakshi (2016) and Nguyen et al. (2021) show that the income-obesity gradient has been tilting away from higher socio-economic status (SES) groups but, they too, do not explore the role of diets.

In this paper, we analyze the association between processed food consumption and obesity in fast-growing peri-urban areas. In India, fast-paced urbanization, improved infrastructure, and the growth of small towns have blurred the boundaries between rural and urban areas (Denis et al., 2012; Pingali et al., 2019), leading to the creation of complex rural–urban interfaces (RUI). The RUI stretch from the outskirts of cities to areas that are conventionally defined as rural. The RUI – where distinct characteristics of rural and urban areas merge and evolve – provides easy access to diverse foods, occupation transitions, and changing lifestyles. These factors create an environment that facilitates dietary transition and obesity prevalence, especially among the poor. In this paper, we explore the correlations between processed food calories and obesity prevalence in such a setting. To this end, we utilize a unique primary cross-section survey that collected socio-economic, diet, and body mass index (BMI) information from households and women living in the RUI of the mega-city of Bangalore (Karnataka, India).

We make two contributions to the literature. First, we show that accounting for different levels of industrial food processing can enhance our understanding of the dietary correlates of obesity in LMICs. We use a globally comparable classification system (NOVA) to disentangle the correlations between calories consumed from different types of processed foods – semi-processed foods (SPF) vs. ultra-processed foods (UPF) – and obesity prevalence (Monteiro, 2009). Studies in high-income countries show that the excess consumption of UPF such as sweetened beverages, ready-to-eat meals, and fast-foods is correlated with the prevalence of obesity (de Amicis et al., 2022; Askari et al., 2020; Monteiro et al., 2018; Nardocci et al., 2021). Studies for LMICs show that increased intake of SPF such as calorie sweeteners, edible oils, and livestock products is associated with the prevalence of obesity (Cockx et al., 2018; Joshi et al., 2019; Popkin et al., 2012; Shetty, 2002). In our paper, we find a similar within-country relationship. Calories from UPF are correlated with the prevalence of obesity among women in higher SES groups and with higher education levels. Among women from lower-middle SES groups, excess consumption of calories from SPF is associated with the prevalence of obesity, especially among ration card holders. We hypothesize that the relationship arises due to differences in affordability of processed foods. For many of the poor in India, the Public Distribution System (PDS) makes SPF available at highly subsidized prices. This encourages them to purchase and consume SPF. Among the rich, UPF consumption is driven by its affordability and the high opportunity cost of time spent preparing meals. We also show that SPF calories and obesity are correlated for individuals in households that consume more calories than their recommended daily allowance (RDA). This suggests that overconsumption could be one of the underlying relationships linking obesity and processed foods.

Second, we find that higher physical intensity of occupation is correlated with a lower prevalence of obesity (Dang et al., 2019; Mo et al., 2022; Monda et al., 2008). Employment in labor-intensive jobs is associated with lower correlations between obesity and the consumption of calories from SPF. Among older women, who are typically less physically active, the correlation between UPF and obesity is stronger than among younger women. Thus, physical activity appears to play a role that is moderated by age. In addition, older women are typically more empowered in Indian households and hence can control their food intake better than younger women (Chorghade et al., 2006; Rao et al., 2020).

Together, our results highlight the need for interventions that incentivize consumption of healthy diets and spotlight the importance of improving physical activity in similar RUI contexts. Here, rapid urbanization, combined with a sedentary environment and an unhealthy food environment interact to influence obesity prevalence. Stemming the latter with information, knowledge, and opportunity to improve one's diets and physical activity is in urgent need and an important way forward to avoid the nutrition transition from undernutrition to obesity among the poor.

The rest of the paper is structured as follows. We discuss the recent trends in diet transition and obesity in India in Section 2. In Section 3, we discuss our study area and sampling technique, describe the data, and elaborate on the sample characteristics. Section 4 explains the empirical method employed and section 5 discusses the results, limitations, and potential policy implications. Lastly, we summarize our findings and draw conclusions in section 6.

2. Background

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

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

Studies on urban diets in India have identified changing dietary patterns towards processed foods. Daniel et al. (2011) find that dietary patterns in two large cities in India – Mumbai (West India) and Trivandrum (South India) – are characterized by excess consumption of fried snacks and sweets. Satija et al. (2015) find that there is a higher intake of savory snacks and sweets among factory workers in India. Rathi et al. (2017) find that at least half of adolescents living in Kolkata consume three or more servings of energy-dense snacks and beverages per day. Using a large longitudinal dataset on purchased consumer goods, Law et al. (2019) find an increasing trend in the purchase of sweet and salty snacks, edible oils, and other processed foods among urban households in India. Sharma et al. (2020) and Tak et al. (2022) find that processed food consumption is higher among rich urban households. Diets that are rich in sugar, salt, oil, and animal food are found to be positively associated with the incidence of obesity (Daniel et al., 2011; Green et al., 2016; Satija et al., 2015). However, it is not clear from these studies whether obesity results from the excess consumption of SPF such as sugar, salt, oil, and livestock products, or whether it is caused by the excess consumption of UPF.

Why should this matter? First, at lower to moderate income levels SPF are likely to be consumed in greater quantity than UPF since they may be more affordable. In India, sugar is made available at a relatively stable and low prices by the PDS, and sweetened beverages are widely available in markets and retail outlets. Some SPF can be easily prepared at home (e.g. Indian sweets and snacks), whereas most UPF (e.g. pizza,

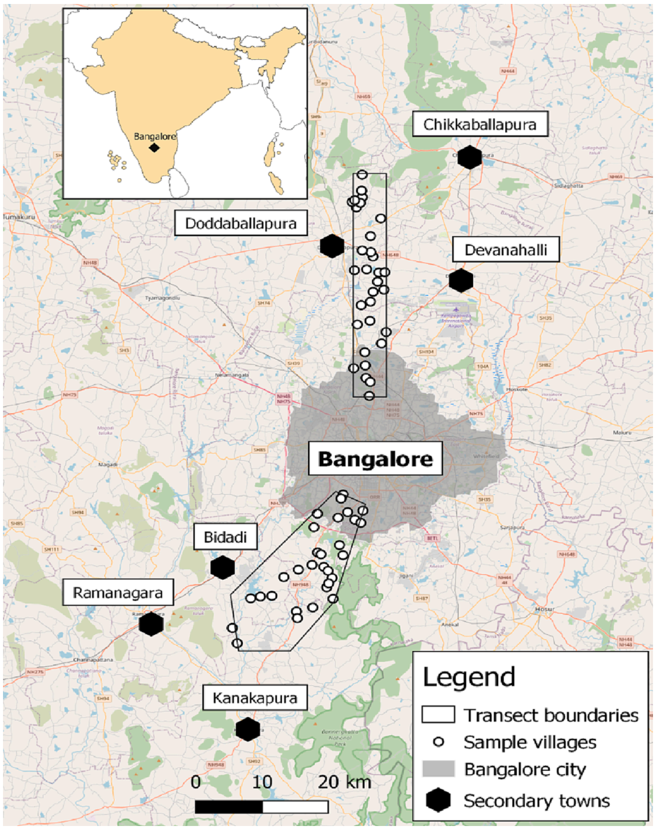

Fig. 1. Study area, research transects, and sample villages/urban-wards.

burgers, fries, etc.) have to be purchased outside at fast-food outlets and are expensive. Thus, among lower-middle SES groups, increased income associated with urban growth may initially enable individuals to purchase and consume more SPF, while UPF remain largely out of reach. Second, the opportunity cost of the time required to prepare meals at home increases with increasing SES. Hence, in the RUI, individuals in high SES groups consume UPF to save time, while individuals in the lower-middle SES group may choose to consume more SPF relative to UPF. If this is true, then if there is an association between UPF and obesity, it will be stronger among higher SES groups, while obesity among lower-middle SES groups is associated with access to more affordable SPF.

2.2. Obesity in India's rural–urban interface (RUI)

Pingali and Khwaja (2004) propose that the speed of shift from the first stage to the second stage of the dietary transition depends on the speed of urbanization of the location. They hypothesize that an urban environment improves both access to and affordability of diverse foods. In India, the emergence of fast-growing small towns has been the major driver of urban population growth in the recent decade (Denis et al., 2012). These small towns affect the living standards and nutritional status of people in nearby rural areas (Aiyar et al., 2021b; Gibson et al., 2017; Rao et al., 2006). As a result, India's urbanization patterns are polycentric, with effects extending from big cities to surrounding small towns and then spilling over into the surrounding rural areas. For example, in the RUI surrounding Bangalore, it is common to see households diversify their livelihood strategies to the off-farm sector even while at least one member remains engaged on the farm (Steinhübel and von Cramon-Taubadel, 2020). The resulting increased income from livelihood diversification allows for a dietary transition and an increased frequency of eating out (Rahman and Mishra, 2020; Sauer et al., 2021).

Changing occupation structure and access to better infrastructure and transportation facilities in the RUI lead to reduced engagement in labor-intensive activities and increasingly sedentary lifestyles. In combination with increased calorie consumption as a result of dietary transition, this creates an imbalance between calorie consumption and expenditure which, all other things being equal, is associated with the increased prevalence of obesity. In the following we provide evidence on how dietary transition to processed foods combined with rapid urbanization is associated with greater obesity in the RUI of Bangalore.

2.3. Bangalore

Bangalore is a rapidly urbanizing mega-city situated in the southern state of Karnataka. Currently around 13 million people are estimated to be residing in Bangalore city (PopulationU, 2022). In the last six decades, the geographical area of the city has expanded more than tenfold from 69 to 741 sq. km (Sudhira et al., 2007), driven by the growth of the industrial, service, and information technology (IT) sectors (Varkey, 2018). Several secondary towns located within a roughly 40-kilometer radius of Bangalore and highways connecting them with each other and to Bangalore have led to a rise in urbanization in the entire region (Directorate of Census Operations Karnataka, 2011). Bangalore exerts a rapidly growing demand for diverse food items from nearby peri-urban and rural areas and serves as a central hub from where the food is distributed. The prevalence of obesity among women in Bangalore increased from 32 percent (2015–16) to 40.1 percent (2019–20) (NFHS-5, 2021). Over the same period, modern retail stores and fast-food outlets have emerged and expanded in Bangalore (Surie and Sami, 2017). The rapid rise in access to food markets reflects the growing demand for convenience and processed foods (Demmler et al., 2018). In addition, the Government of Karnataka provides subsidized ration cards to procure SPF such as oil, sugar, etc. for disadvantaged families (Government of Karnataka, 2013).[2] Urbanization and the resulting livelihood transitions in Bangalore have shaped the food systems and dietary patterns in a way that might increase the propensity for overconsumption and hence the prevalence of obesity.

3. Study area, sampling, and data description

3.1. Study area and sampling design

Our study area in the RUI of Bangalore consists of two research transects. The first transect extends away from Bangalore to the north, and the second transect extends towards the southwest (two polygons in Fig. 1). These transects are surrounded by several secondary towns. Improved access to these urban centers provides households with opportunities to engage in income-generating farm and off-farm employment across the region (Steinhübel and von Cramon-Taubadel, 2020). Thus, the livelihood strategies of many households located in the RUI of Bangalore combine farm and off-farm employment. Such diversification in livelihood strategies is typically associated with increased income (Haggblade et al., 2010). Higher incomes, in turn, enable the purchase of SPF and UPF from a wide range of food outlets from mom & pop stores to hypermarkets, all of which are present in the Bangalore region (Surie

[2] The Government of Karnataka categorizes households as priority or non-priority based on measures of economic status (Government of Karnataka, 2013). Priority households receive Anthyodaya Anna Yojana (AAY) or Below Poverty Line (BPL) cards. In addition to subsidized staples such as rice and wheat, AAY and BPL cards entitle households to receive sugar, oil, certain pulses, and other region-specific food items at subsidized prices. Non-priority households are not eligible for subsidized food under the public distribution system (PDS). However, if they feel that they are food insecure, they can register for Above Poverty Line (APL) cards to receive a small quantity of subsidized grains such as rice.

and Sami, 2017). A variety of fast-food outlets also exist within these transects and in the surrounding small towns, creating easier access to UPF. Furthermore, improvements in infrastructure, transport facilities, and access to off-farm employment in the region have enabled many local inhabitants to pursue more sedentary lifestyles. Hence, the RUI of Bangalore, a space influenced by urbanization, dietary and occupational transition, and lifestyle changes, provides an ideal setting to explore how calories consumed from SPF and UPF are associated with the prevalence of obesity.

For our empirical analysis, we use the data from a socio-economic survey of 1275 households conducted between December 2016 and May 2017 in the RUI of Bangalore. We applied a two-stage stratified random sampling method to ensure that the sample households represent the urbanization pattern in this area. In the first stage, all the villages in each transect were divided into three strata (urban, peri-urban, and rural) using the "Survey Stratification Index (SSI)" (Hoffmann et al., 2017).[3] Then, in each of these strata, sample villages/urban-wards were randomly selected proportional to their size (in total 61 villages/urban-wards). In the second stage, households were randomly selected in each village/urban-ward again proportional to their size using the village household lists maintained by the publicly run village kindergartens.

Data on the socioeconomic, demographic, livelihood characteristics, etc. of the sample households were collected from the household decision-maker using a comprehensive questionnaire. The caregiver of the family was interviewed to collect information on household food consumption up to 14-days before the interview.[4] Anthropometric measurements such as height and weight were recorded for all the women living in the sample households, except for pregnant and nursing women. Written consent was obtained from respondents before conducting the interview and taking anthropometric measurements. We concentrate on obesity among women because women are usually the main caregivers and food shoppers, and face time constraints in Indian society. Increased opportunities to work outside the home make them sensitive to the incentives to save time in food preparation by increasing the consumption of processed foods and meals eaten outside the home. These alternatives have implications not just for their own health but for that of other family members (Regmi and Dyck, 2001; Sauer et al., 2021). Harttgen et al. (2013) find that the nutrition status of women is directly correlated with that of other household members.

3.2. Data description

3.2.1. Survey overview

While our survey consisted of 1275 households, demographic and food consumption data were available for only 1121 households.[5] Of these, we had to drop 22 households owing to extreme calorie consumption values which we consider to be outliers.[6] Hence, our sample consists of 1099 households. A total of 1973 women were recorded as members of these households. Even after multiple visits to households, we could only collect anthropometric measurements for 1401 of these women. Hence, anthropometric data are not available for 29 percent of the women in our sample. To ensure that there is no sample selection bias, we compare the characteristics of women for whom anthropometric data are/are not available using logistic regression (Appendix Table A1). The results show that women for whom anthropometric data are available are on average more likely to be less educated, members of smaller households, have scheduled caste and scheduled tribe (SC&ST) caste, and have better access to safe drinking water. Controlling for these factors reduces the sample by a further 56 observations due to missing covariates. The results of the t-tests summarized in Appendix Table A2 suggest that missing covariates have no significant influence on a woman's BMI. Our final sample consists of 1345 women for whom complete data on BMI, processed food consumption, and covariates are available. In Table 1, we present summary statistics for the final data set.

3.2.2. Dependent variable

We use anthropometric measurements to capture obesity. In line with other studies in South Asia, women with BMI $\geq$25 are considered as obese (Wen et al., 2009; WHO-Western Pacific Region, 2000). In our sample of women in the RUI of Bangalore, 35 percent are obese (Table 1). The distribution of BMI in this sample is slightly right skewed (Appendix Fig. A1a) and displays an inverse U relationship with age (Appendix Fig. A1b). This is similar to the BMI distribution among Indian women found in Aiyar et al. (2021a), who plot BMI distributions for women across urban and rural India. In Table 2 (column 3), we provide the disaggregated summary of obesity prevalence by socio-economic characteristics of the sample. We see that the prevalence of obesity is higher among women in households with higher SES, older women, and among women who are housewives and earn incomes outside the house. These points are consistent with the idea that obesity is correlated with both income status and the opportunity costs of preparing meals food at home.

3.2.3. Independent variable

Our main variables of interest are the calories consumed from SPF and UPF. Moubarac et al. (2014) review five different processed food classification systems from different parts of the world. They suggest that the NOVA food classification system, which accounts for different levels of industrial processing, is globally comparable and most suited to the design of dietary guidelines. In addition, the NOVA food classification system is widely used in the literature to study the relationship between processed food consumption and health (Juul et al., 2018; Moubarac et al., 2013). We thus adopt the NOVA classification system, which classifies food items into three groups according to the *"nature,*

[3] Survey stratification index (SSI) is a composite index constructed using two variables – distance to Bangalore city center and building density. The strata – urban, peri-urban, and rural – are defined as the terciles of SSI.

[4] The survey instrument for the 14-day recall household food consumption data was prepared based on the Food and Agricultural Organization (FAO) and World Bank guidelines for household food consumption expenditure survey in low- and middle-income countries (LMICs) and further adjusted after pre-testing to include all the locally consumed food items (FAO and World Bank, 2018). Two concerns arise when we use recall-based food consumption data at the household level to study its association with obesity in specific demographics (in our case women) within the household. The first is that there might be differences between the ultra-processed food consumed at household and individual level. Da Louzada et al. (2017) show important agreements between the estimates of ultra-processed foods (UPF) consumed at household and individual level data, particularly when the "share of total energy" is used to estimate the two. Since we use the "share of calories/energy" as the main explanatory variable, we are confident that household level consumption of processed foods can be a good proxy of individual level intake. The second is that the caregiver might not be able to report all food items consumed, especially if they are purchased outside the home by other household members. To reduce this measurement error, we followed (FAO and World Bank, 2018) and collected information on how many household members regularly consumed meals away from home (MAFH) in the past 14-days. This information was included as a control variable in the subsequent regression analysis.

[5] Of the missing 154 households, the decision-maker part of the questionnaire was not administered for 47 and the food consumption part of the questionnaire was not administered for 78. This resulted in dropping 125 households that had either food consumption or household demographics data, but not both. Among the households in which both the decision-maker and food consumption parts of the questionnaire were administered, 21 and 8 households had to be dropped because of incomplete/partial information on questions related to food consumption and household demographic characteristics, respectively.

[6] We consider observations in the 1st percentile (<=979 Kcal/AE/day) and 99th percentile (>=11379 Kcal/AE/day) as extreme.

Table 1
Summary statistics of the sample women and households.

Variable	Unit	Mean	Min	Max
Dependent variable				
Body mass index (BMI)	Kg/m2	23.39	11.42	43.73
Obesity	BMI>=25 Kg/m2	0.35	0	1
Main explanatory variable				
Calorie for NOVA food group	Unprocessed and minimally processed foods (Un-PF) (%)	74.48	25.03	98.43
	Semi-processed food (SPF) (%)	17.88	1.56	63.5
	Ultra-processed food (UPF) (%)	4.10	0	38.76
Individual-level characteristics				
Age	Years	37.9	15	90
Marital status	1. Married	0.80	0	1
	2. Unmarried	0.11	0	1
	3.Divorced/widowed	0.09	0	1
Education	Years	6.3	0	23
Education level	1. Illiterate	0.36	0	1
	2. High school (up to 9th grade)	0.24	0	1
	3. SSC/HSC (10th-12th grade) or Diploma	0.31	0	1
	4. General/professional graduate/postgraduate	0.09	0	1
Main occupation	1. Housewife	0.61	0	1
	2. Office work	0.11	0	1
	3. Labor-intensive work	0.13	0	1
	4. Student	0.07	0	1
	5.Others	0.08	0	1
Number of children	Number of children a woman has	2.10	0	11
Household-level characteristics				
Family size	Count of household members	5.15	1	19
Religion	Dummy: 1. Hindu; 0. Others	0.95	0	1
Caste	1. General	0.45	0	1
	2. Schedule caste and schedule tribe (SC&ST)	0.27	0	1
	3. Other backward castes (OBC)	0.28	0	1
Economic status	Count of durable assets owned by the household	5.94	0	11
Economic status	1. Asset index - Quartile 1	0.36	0	1
	2. Asset index - Quartile 2	0.28	0	1
	3. Asset index - Quartile 3	0.22	0	1
	4. Asset index - Quartile 4	0.14	0	1
Ration card	1. No ration card	0.11	0	1
	2. Above poverty line (APL) ration card	0.07	0	1
	3. Below poverty line (BPL) ration card	0.82	0	1
Food source	Market purchase from modern food outlets (%)	22.31	0	100
Person buying food	1. Adult female	0.26	0	1
	2. Adult male	0.57	0	1
	3. Anybody in the family	0.17	0	1
Meals away from home (MAFH)	Count of number of household members regularly eating meals away from home	0.40	0	4
Safe drinking water	Dummy: 1. Yes; 0. No	0.93	0	1
Toilet	Dummy: 1. Yes; 0. No	0.96	0	1
Calorie adequacy ratio	1. Women in calorie-adequate households	0.67	0	1
	2. Women in calorie-inadequate households	0.33	0	1
Location characteristics				
Distance to Bangalore	Kilometer distance from village center to Bangalore city center	25.54	6.97	48.54
Location	Dummy: 1. North; 0. South	0.51	0	1
Observations		1345		

extent, and purpose" of industrial processing (Monteiro, 2009). Information on processing includes the physical, chemical, and biological treatments that food items undergo after separating them from their natural form and before they are consumed as dishes or ingredients. The three food groups of the NOVA classification system are (i) Unprocessed and minimally processed foods (Un-PF), (ii) Processed culinary or food industry ingredients (which we call semi-processed foods – SPF), and (iii) Ultra-processed foods (UPF). Monteiro et al. (2010) provide a detailed description of these three food groups.[7] We calculate the share of calories consumed in each of the NOVA food groups using the 14-day recall household food consumption data provided by the caregiver.[8]

Using the 14-day recall food consumption data, the reported quantities of all food items consumed are converted into caloric values using nutrient conversion factors provided in the Indian Food Composition Tables (IFCT) (Longvah et al., 2017).[9] The calorie values of each food item are added to produce cal_j, the total amount of calories consumed by household j. We categorize all the food items, their quantities, and respective calories into three groups (k) of the NOVA classification system – Un-PF (m), SPF (s), and UPF (u). The calories within each group k are added to produce $q_{k,j}$, the calories consumed in each NOVA food group k by household j. The share of calories consumed in food group k by household j is computed by dividing $q_{k,j}$ by cal_j.

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

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

We also calculate the quartiles for each food group using $Kcal_{k,j}$. Since we are interested in the relationship between processed food consumption and obesity, we focus on the share of calories from the corresponding SPF and UFP food groups – $Kcal_{s,j}$ and $Kcal_{u,j}$. In Table 1, we can see that 74.5 percent of the calories in our sample households' diets come from Un-PF group. Of these calories, 63 percent derive from staples such as rice. Compared with other studies, mostly from developed countries (Monteiro et al., 2018; Moubarac et al., 2013; Poti et al., 2015), which find that 25 to 39 percent of calories consumed come from Un-PF, our sample households consume relatively more calories from Un-PF. On average, the two processed food groups—SPF and UPF—account for around 17 and 4 percent of the total calories consumed by our sample households, respectively. However, the shares of SPF and UPF vary widely among households, ranging up to maximum values of 63,5 and 38.3 percent, respectively (see distributions in Appendix Fig. A2). Hence, the households in our sample are in the midst of the dietary transition outlined by Pingali and Khwaja (2004) for India. The majority of the calories that they consume derive from Un-PF, but

[7] In Appendix Table 3 we categorize all of the food items consumed by our sample households according to the NOVA classification.

[8] Despite concerns about possibly uneven intra-household distributions of food consumption, we are confident that our data on household-level calorie consumption is a good proxy for consumption of calories by the women in these households. We base this conclusion on a systematic review by Berti (2012) who finds that intra-household distribution of dietary energy/calories is relatively equitable in most LMICs. In addition, Coates et al. (2017) and Coates et al. (2018) find that intra-household inequities in food distribution are less pronounced for calories than for other nutrients. Related studies in the food security literature that show the calorie intake is lower for women within households (Gupta et al., 2020; Harris-Fry et al., 2018). Indeed, based on personal experience with surveys in India, we believe that women are consuming less than the average household member. This would lead to under- rather than overestimation of the relationship between calories from processed foods and women's body mass index (BMI).

[9] For food items for which calorie conversion factors are not available, we use USDA food composition tables (USDA, 2021).

Table 2
Disaggregated summary statistics of outcome and main explanatory variables by the socio-economic characteristics the sample.

Variable		Mean obesity	Mean share of calories from SPF	Mean share of calories from UPF
Asset index	Quartile 1	0.24***	16.9	3.92
	Quartile 2	0.36	17.42	3.90**
	Quartile 3	0.41*	18.18***	4.68*
	Quartile 4	0.50***	20.86***	4.01
Main occupation	Housewife	0.39	17.88	4.17
	Office work	0.37**	18.76**	4.67***
	Labor-intensive work	0.25***	16.53***	3.25*
	Student	0.12***	20.03**	4.17
	Others	0.36	17.15	4.12
Education level	No education	0.36	16.59***	3.6
	Primary education	0.36	18.14	3.99**
	Secondary education	0.32	18.66	4.63
	Higher education	0.32	19.88***	4.55**
Ration card type	No ration card	0.36**	20.73	5.43
	APL ration card	0.51***	21.69***	4.73*
	BPL ration card	0.33	17.19***	3.86***
Age	<=15 to < 25 years	0.15***	18.32	4.35
	>=25 to < 35 years	0.36	17.95	4.75***
	>=35 to <=50 years	0.41	17.93	3.84*
	>50 to <=90 years	0.41***	17.21	3.37***
Calorie adequacy	Calorie-inadequate households	0.32	18.15	3.98
	Calorie-adequate households	0.36	17.75	4.15

Notes: *** significant at P-value < 0.01, ** significant at P-value < 0.05, * significant at P-value < 0.1. The differences between means of different categories of variables mentioned in different rows are presented in the table. For example, 0.24*** (row 1, column 3) represents a significant difference between obesity prevalence among women at Quartile 1 and Quartile 2 of the asset index. SPF – semi-processed foods, UPF – ultra-processed foods, APL – above poverty line, BPL – below poverty line.

the shares of SPF and UPF are substantial.

In Table 2 (columns 4 and 5), we see that the mean share of calories consumption from SPF and UPF is higher among women in higher asset quartiles. This suggests that processed foods are luxury goods with high income elasticities of demand. Similarly, women with own income consume higher shares of calories from processed foods. The consumption of SPF and UPF is the higher among those with high education and among those who have ration cards. We provide socio-economic correlates of SPF and UPF consumption among our sample women in Appendix Table A4.

3.2.4. Calorie adequacy ratio

To estimate the relationship between processed food calories and obesity among women in households whose calorie consumption meets or do not meet their RDA, we calculated the adequacy of the calories consumed by the households. We use standardized calorie intake recommendations by the Indian Council of Medical Research (ICMR) that account for the age, gender, and physical activity level of an individual to calculate the adequacy of a household's calorie consumption. First, information on the age, gender, and physical activity levels of all family members above six months are used to calculate the recommended quantities of calories for each household member. We use the main occupation as a proxy for the physical activity levels of adult members aged 18 and older.[10] Second, the individual RDAs of all household members are added to produce an RDA estimate for the household. Third, the total (actual) quantity of calories consumed by the household was calculated using food consumption data as described above (Section 3.2.3). Finally, the total quantity of calories consumed by the household was divided by the total RDA for calories to produce a calorie adequacy ratio. Households for which the calorie adequacy ratio is greater (less) than one are considered to be a calorie-adequate (inadequate). In our sample, 67 (33) percent of women live in calorie-adequate (inadequate) households (Table 1).

3.3. Control variables

Besides SPF and UPF, we also control for the individual- and household-level characteristics of women in our estimations. The women in our sample are on average 37 years old, have six years of education, and two children (Table 1). 80 percent are married. 61 percent report being housewives, 10 percent engage in relatively low-intensity work in the public or private sector, 13 percent do labor-intensive work such as agriculture or casual labor, 7 percent are students, and the remaining 9 percent either do not or are unable to work.

Among the household-level controls summarized in Table 1, we see that the average household size is five. The variables related to caste and religion control for the influences of social status and economic opportunities. In our sample, 95 percent are Hindu, 45 percent belong to the General caste, 27 percent belong to the SC&ST, and 28 percent belong to the other backward castes (OBC) group. We include the number of durable assets owned by the household as a measure of economic status.[11]

We also control for factors that are directly related to household food

[10] We follow Dang et al. (2019) to categorize different occupations into low, moderate, and high physical intensity. For household members below 18 years of age, no physical activity level is considered in calculating the recommended dietary allowance (RDA) for calories, as it was not one of the criteria required to calculate RDA by the Indian Council of Medical Research (ICMR).

[11] The asset index is calculated following "The New Socio-economic Classification" system provided by "The Market Research Society of India" in 2011. The index is constructed based on a household's ownership/possession of assets belonging to a list of 11 "consumer durables" (MRSI, 2011).

Table 3
Processed foods calorie consumption and obesity – Probit model.

Variables	Model 1	Model 2
	Obesity	Obesity
SPF calories (%) (ref. Quartile 1)		
Quartile 2	0.02 (0.09)	−0.03 (0.11)
Quartile 3	0.09 (0.10)	0.02 (0.11)
Quartile 4	**0.26** (0.11)**	0.13 (0.13)
UPF calories (%) (ref. Quartile 1)		
Quartile 2	0.14 (0.11)	0.14 (0.12)
Quartile 3	**0.22** (0.10)**	**0.24* (0.12)**
Quartile 4	0.09 (0.11)	0.03 (0.11)
Age (years)		0.01 (0.00)
Education (years)		−0.00 (0.01)
Marital status (ref. Married)		
Unmarried		−0.17 (0.15)
Divorced/widowed		0.03 (0.17)
Main occupation (ref. Housewife)		
Office work		−0.01 (0.11)
Labor-intensive work		**−0.20** (0.10)**
Student		**−0.45* (0.24)**
Others		−0.19 (0.17)
Number of children (count)		**0.10*** (0.03)**
Household members (count)		0.01 (0.01)
Religion (dummy - Hindu)		−0.18 (0.14)
Caste (ref. General)		
Schedule caste and schedule tribe (SC&ST)		−0.05 (0.08)
Other backward castes (OBC)		**0.22** (0.09)**
Assets (count) (ref. Quartile 1)		
Quartile 2		**0.36*** (0.09)**
Quartile 3		**0.38*** (0.11)**
Quartile 4		**0.48*** (0.12)**
Ration card (ref. No ration card)		
Above poverty line (APL) ration card		0.25 (0.20)
Below poverty line (BPL) ration card		0.05 (0.13)
Grocery purchase from modern food outlets (%)		0.00 (0.00)
Main grocery shopper (ref. Adult female)		
Adult male		−0.10 (0.10)
Anybody in the family		0.04 (0.11)
Meals away from home (MAFH) (count)		−0.08 (0.06)
Safe drinking water (dummy - yes)		−0.05 (0.15)
Toilet (dummy - yes)		0.57 (0.36)
Distance to Bangalore (km)		**−0.03*** (0.00)**
Location (dummy - North)		**0.28*** (0.09)**
Mean obesity	0.35	0.35
Pseudo R-squared	0.01	0.11
Observations	1,345	1,345

Notes: Robust standard errors in parentheses. *** P-value < 0.01, ** P-value < 0.05, * P-value < 0.1. Standard errors are clustered at village level. SPF – semi-processed foods, UPF – ultra-processed foods.

consumption such as the food source and the person buying food from the market (Table 1). On average 22 percent of purchased food in our sample comes from modern food markets. In 26 (57) percent of the sample households, the main food purchases are carried out by a female (male) household member. In the remaining 17 percent, any member of the household might buy food from the market. Since women are not the main purchasers of food in many households, one might question whether they, as the caregivers who were our main survey respondents, are in a position to provide accurate information on all of the food purchases in their households. However, we observed that males account for a high share of household food purchases because they are often responsible for purchasing large quantities of staples, typically at monthly intervals. Caregivers can keep track of and accurately recall these bulk purchases by male household members. The caregivers themselves are typically responsible for more frequent purchases of processed foods and perishable fruits and vegetables. An average of 0.4 household members regularly consume meals away from home (MAFH) in our sample households. Over 90 percent of the households have access to safe drinking water and sanitation facilities.

4. Methods

We estimate the relationship between SPF and UPF calorie consumption and obesity using a probit model.[12] We first estimate the relationship between processed foods and obesity without controlling for confounding factors using model 1 (Eq. (1)). Using model 2 (Eq. (2)) we estimate the relationship between processed calorie consumption and obesity conditional on individual, household, and location characteristics.

$$Y_{i,j} = \beta_0 + \alpha P_{i,j} + \varepsilon_{i,j} \tag{1}$$

$$Y_{i,j} = \beta_0 + \alpha P_{i,j} + \beta_{control} X_{i,j} + \beta_{dist} D_{i,j} + \varepsilon_{i,j} \tag{2}$$

Here, i represents individual women in the household j. $Y_{i,j}$ is our outcome of interest, which takes value 1 for obesity if BMI $\geq$25, and 0 otherwise. Both models include a constant β_0 and a stochastic error term ε. The parameters α, $\beta_{control}$ and β_{dist} quantify the effects of variables in the vectors P, X, and D, respectively. The vector P contains quartiles of the share of calories consumed from SPF and UPF ($P = Kcal_{s,j}, Kcal_{u,j}$); X contains the control variables presented in Table 1,[13] and D contains a dummy variable for the research transect (north or south) and a variable that measures the distance from the village center to Bangalore city.

Several studies show that certain sedentary occupation types are associated with higher BMI even when there is an overall decline in energy intake (Dang et al., 2019; Mo et al., 2022; Popkin, 2009). Thus, we also estimate whether the relationship between processed foods and obesity is mediated by the type of occupational activity of women, which we use as a proxy for the work-effort characteristic of the occupation. For this, we estimate model 3 (equation (3)), which includes an interaction variable between the quartiles of share of SPF and UPF calories and the occupation of women, $P \times O = (Kcal_{s,j} \times O, Kcal_{u,j} \times O)$. The coefficient for interaction effect is represented by the superscript " $\times$ " to the parameter α in the equation below.

$$Y_{i,j} = \beta_0 + \alpha P_{i,j} + \alpha^{\times} \left(P_{i,j} \times O_{i,j}\right) + \gamma O_{i,j} + \beta_{control} X_{i,j} + \beta_{dist} D_{i,j} + \varepsilon_{i,j} \tag{3}$$

Similar mediation is also considered to occur between the age of women and obesity prevalence. Older women are considered to have higher propensity for obesity prevalence due to their lower physical mobility and higher control over resources within the household (Hosseini et al., 2020; Muhammad et al., 2022). Thus, we test whether the relationship between processed food calories and obesity prevalence is mediated by age of women using interaction variable $P \times A = (Kcal_{s,j} \times A, Kcal_{u,j} \times A)$ as shown in the model 4 (equation (4)) below.

$$Y_{i,j} = \beta_0 + \alpha P_{i,j} + \alpha^{\times} \left(P_{i,j} \times A_{i,j}\right) + \gamma A_{i,j} + \beta_{control} X_{i,j} + \beta_{dist} D_{i,j} + \varepsilon_{i,j} \tag{4}$$

5. Results

5.1. Relationship between processed foods and obesity

Table 3 presents the regression results for the relationship between processed food calories and obesity. The results for model 1 (column 2 in Table 3) show that, compared with quartile 1, SPF calories at the fourth and UPF calories at the third quartile of consumption are correlated with an increased prevalence of obesity among women. This implies that

[12] As a robustness check, we also estimate this relationship using logistic and linear probability regression models. The results are not affected by the choice of estimation model.

[13] We find that the relationship between processed food calories and obesity is not influenced by total calorie consumption. Results are robust to including 'total household calorie consumption' (measured as Kcal/AE/day). These results are available on request.

Table 4
Processed foods calorie consumption and obesity – Analysis by low- and high-income households.

Variables	Quartile 1	Quartile 2	Quartile 3	Quartile 4
SPF calories (%) (ref. Quartile 1)				
Quartile 2	−0.06 (0.18)	−0.18 (0.19)	−0.32 (0.25)	0.13 (0.35)
Quartile 3	−0.21 (0.21)	−0.00 (0.22)	0.21 (0.27)	0.07 (0.41)
Quartile 4	−0.05 (0.23)	−0.12 (0.20)	**0.56** (0.24)**	0.09 (0.33)
UPF calories (%) (ref. Quartile 1)				
Quartile 2	0.05 (0.19)	0.07 (0.18)	0.38 (0.32)	0.30 (0.28)
Quartile 3	0.25 (0.18)	0.23 (0.20)	−0.05(0.27)	**0.97*** (0.33)**
Quartile 4	−0.15 (0.19)	0.03 (0.18)	0.18 (0.31)	0.17 (0.32)
Controls	*Yes*	*Yes*	*Yes*	*Yes*
Mean obesity	0.24	0.36	0.41	0.5
Pseudo R-squared	0.1	0.14	0.2	0.24
Observations	476	380	303	186

Notes: Robust standard errors in parentheses. *** P-value < 0.01, ** P-value < 0.05, * P-value < 0.1. Standard errors are clustered at village level. SPF – semi-processed foods, UPF – ultra-processed foods.
Controls include age, occupation, marital status, number of children, household size, religion, caste, ration card, share of food purchases from modern retail stores, person buying food from the market, number of household members regularly eating meals away from home, access to safe drinking water, access to toilet, distance to Bangalore city center, and a dummy for research transect.

Table 5
Processed foods calorie consumption and obesity – Analysis by the education level of women.

Variables	No education	Primary education (class 1–9)	Secondary education (class 10–12/ diploma)	Higher education (graduate and post-graduate)
SPF calories (%) (ref. Quartile 1)				
Quartile 2	0.11 (0.19)	−0.12 (0.24)	−0.04 (0.18)	0.04 (0.52)
Quartile 3	0.06 (0.19)	0.00 (0.25)	0.01 (0.22)	−0.69 (0.55)
Quartile 4	0.02 (0.22)	0.17 (0.25)	0.18 (0.18)	−0.38 (0.62)
UPF calories (%) (ref. Quartile 1)				
Quartile 2	0.21 (0.19)	−0.02 (0.21)	−0.06 (0.23)	**1.14* (0.62)**
Quartile 3	0.30 (0.20)	0.05 (0.25)	−0.07 (0.24)	**1.98*** (0.58)**
Quartile 4	−0.04 (0.18)	−0.23 (0.22)	−0.07 (0.23)	**2.05*** (0.54)**
Controls	*Yes*	*Yes*	*Yes*	*Yes*
Mean obesity	0.36	0.36	0.32	0.32
Pseudo R-squared	0.13	0.17	0.16	0.49
Observations	489	325	417	114

Notes: Robust standard errors in parentheses. *** P-value < 0.01, ** P-value < 0.05, * P-value < 0.1. Standard errors are clustered at village level. SPF – semi-processed foods, UPF – ultra-processed foods.
Controls include age, occupation, marital status, number of children, household size, religion, caste, asset quartiles, ration card, share of food purchases from modern retail stores, person buying food from the market, number of household members regularly eating meals away from home, access to safe drinking water, access to toilet, distance to Bangalore city center, and a dummy for research transect.

women who consume higher shares of calories from SPF and UPF are more likely to be obese than women who consume relatively lower shares. These correlations are in line with a large part of the literature that shows processed foods are one of the main dietary correlates of obesity prevalence (Asfaw, 2011; Moradi et al., 2021; Moubarac et al., 2013; Popkin and Ng, 2022; Reardon et al., 2021).

The results for model 2 (column 3 in Table 3) that estimates the relationship between processed foods and obesity after controlling for individual and household characteristics show that only the relationship between UPF and obesity is statistically significant. At the individual level, certain occupational activities have a significant association with the reduction in obesity prevalence in this setting. That is, relative to housewives, whom we consider to have medium-intensity activities according to Dang et al. (2019), women engaged in labor-intensive occupations such as farming or casual labor and students are less likely to be obese. The more children a woman has, the higher the likelihood of obesity prevalence (Balarajan and Villamor, 2009). As identified by several studies (Meenakshi, 2016; Pingali et al., 2019; Subramanian et al., 2011), higher economic status of the household increases the prevalence of obesity in our setting. Women in the OBC caste category

Table 6
Processed foods calorie consumption and obesity – Analysis by households without and with ration cards.

Variables	No ration card	APL ration card	BPL ration card
SPF calories (%) (ref. Quartile 1)			
Quartile 2	**−2.38*** (0.64)**	−0.03 (0.80)	0.07 (0.12)
Quartile 3	**−1.06* (0.55)**	−0.85 (0.54)	0.06 (0.11)
Quartile 4	**−1.67*** (0.56)**	−0.49 (0.70)	**0.26* (0.14)**
UPF calories (%) (ref. Quartile 1)			
Quartile 2	**−1.06* (0.58)**	1.04 (0.73)	0.15 (0.13)
Quartile 3	0.80 (0.52)	−0.80 (0.52)	0.23 (0.14)
Quartile 4	0.59 (0.48)	−0.66 (0.73)	0.08 (0.12)
Controls	*Yes*	*Yes*	*Yes*
Mean obesity	0.36	0.51	0.33
Pseudo R-squared	0.35	0.35	0.11
Observations	154	85	1,106

Notes: Robust standard errors in parentheses. *** P-value < 0.01, ** P-value < 0.05, * P-value < 0.1. Standard errors are clustered at village level. APL – Above poverty line, BPL – Below poverty line, SPF – semi-processed foods, UPF – ultra-processed foods.
Controls include age, education, occupation, marital status, number of children, household size, religion, caste, asset index, share of food purchases from modern retail stores, person buying food from the market, number of household members regularly eating meals away from home, access to safe drinking water, access to toilet, distance to Bangalore city center, and a dummy for research transect.

Table 7
Processed foods calorie consumption and obesity – Analysis by calorie-inadequate and calorie-adequate households.

Variables	Calorie-inadequate	Calorie-adequate
SPF calories (%) (ref. Quartile 1)		
Quartile 2	−0.01 (0.19)	−0.03 (0.14)
Quartile 3	−0.03 (0.22)	0.03 (0.14)
Quartile 4	−0.18 (0.20)	**0.30** (0.15)**
UPF calories (%) (ref. Quartile 1)		
Quartile 2	0.14 (0.20)	0.13 (0.15)
Quartile 3	0.35 (0.21)	0.18 (0.15)
Quartile 4	−0.14 (0.19)	0.07 (0.13)
Controls	*Yes*	*Yes*
Mean obesity	0.32	0.36
Pseudo R-squared	0.09	0.15
Observations	443	902

Notes: Robust standard errors in parentheses. *** P-value < 0.01, ** P-value < 0.05, * P-value < 0.1. Standard errors are clustered at village level. SPF – semi-processed foods, UPF – ultra-processed foods.
Controls include age, education, occupation, marital status, number of children, household size, religion, caste, asset index, ration card, share of food purchases from modern retail stores, person buying food from the market, number of household members regularly eating meals away from home, access to safe drinking water, access to toilet, distance to Bangalore city center, and a dummy for research transect.

Table 8
Processed foods calorie consumption and obesity – moderation by the occupational activity of women.

Variables	Obesity (Model 3)
SPF calories (%) (ref. Quartile 1)	
Quartile 2	−0.00 (0.15)
Quartile 3	0.07 (0.13)
Quartile 4	**0.24* (0.14)**
SPF calories (%) X Main occupation	
Quartile 2 X Office work	0.13 (0.39)
Quartile 2 X Labor-intensive work	0.22 (0.34)
Quartile 2 X Student	**−1.13** (0.56)**
Quartile 2 X Others	−0.11 (0.42)
Quartile 3 X Office work	−0.12 (0.38)
Quartile 3 X Labor-intensive work	−0.14 (0.25)
Quartile 3 X Student	−0.16 (0.42)
Quartile 3 X Others	−0.12 (0.33)
Quartile 4 X Office work	0.22 (0.38)
Quartile 4 X Labor-intensive work	**−0.69* (0.41)**
Quartile 4 X Student	**−1.52*** (0.55)**
Quartile 4 X Others	0.02 (0.34)
UPF calories (%) (ref. Quartile 1)	
Quartile 2	0.13 (0.13)
Quartile 3	0.19 (0.14)
Quartile 4	0.09 (0.13)
UPF calories (%) X Main occupation	
Quartile 2 X Office work	0.14 (0.40)
Quartile 2 X Labor-intensive work	0.09 (0.35)
Quartile 2 X Student	−0.10 (0.50)
Quartile 2 X Others	−0.03 (0.40)
Quartile 3 X Office work	0.17 (0.41)
Quartile 3 X Labor-intensive work	0.37 (0.34)
Quartile 3 X Student	0.54 (0.43)
Quartile 3 X Others	−0.19 (0.39)
Quartile 4 X Office work	−0.16 (0.37)
Quartile 4 X Labor-intensive work	−0.31 (0.37)
Quartile 4 X Student	0.14 (0.54)
Quartile 4 X Others	−0.00 (0.40)
Main occupation (ref. Housewife)	
Office work	−0.11 (0.37)
Labor-intensive work	−0.17 (0.28)
Student	0.03 (0.56)
Others	−0.05 (0.38)
Controls	*Yes*
Mean obesity	0.35
Pseudo R-squared	0.12
Observations	1,345

Notes: Robust standard errors in parentheses. *** P-value < 0.01, ** P-value < 0.05, * P-value < 0.1. Standard errors are clustered at village level. SPF – semi-processed foods, UPF – ultra-processed foods.
Controls include age, education, marital status, number of children, household size, religion, caste, asset index, ration card, share of food purchases from modern retail stores, person buying food from the market, number of household members regularly eating meals away from home, access to safe drinking water, access to toilet, distance to Bangalore city center, and a dummy for research transect.

are more likely to be obese than those in the General caste category. In line with the findings from Aiyar et al. (2021b), we find that women living further away from Bangalore city are less likely to be obese. Steinhübel and von Cramon-Taubadel (2020) show that there are significant differences in household characteristics between the northern and southern transect of our study setting. The households in the northern transect are more likely to use modern agricultural practices, have relatively higher shares of off-farm employment, and more educated household heads than the households in the southern transect. These differences likely lead to higher incomes and more sedentary lifestyles among women in the northern transect, which might contribute to explaining the higher prevalence of obesity observed in the northern research transect.

Table 9
Processed foods calorie consumption and obesity – moderation by age.

Variables	Obesity
SPF calories (%) (ref. Quartile 1)	
Quartile 2	**−0.48* (0.26)**
Quartile 3	−0.36 (0.27)
Quartile 4	−0.47 (0.30)
SPF calories (%) X Age group	
Quartile 2 X Age group (2)	0.25 (0.31)
Quartile 2 X Age group (3)	**0.71*** (0.27)**
Quartile 2 X Age group (4)	0.40 (0.35)
Quartile 3 X Age group (2)	0.10 (0.32)
Quartile 3 X Age group (3)	**0.65** (0.32)**
Quartile 3 X Age group (4)	0.27 (0.38)
Quartile 4 X Age group (2)	**0.73** (0.35)**
Quartile 4 X Age group (3)	**0.68** (0.31)**
Quartile 4 X Age group (4)	0.61 (0.44)
UPF calories (%) (ref. Quartile 1)	
Quartile 2	0.16 (0.27)
Quartile 3	−0.08 (0.31)
Quartile 4	−0.21 (0.31)
UPF calories (%) X Age group	
Quartile 2 X Age group (2)	−0.11 (0.37)
Quartile 2 X Age group (3)	−0.05 (0.27)
Quartile 2 X Age group (4)	0.18 (0.36)
Quartile 3 X Age group (2)	0.10 (0.36)
Quartile 3 X Age group (3)	0.47 (0.31)
Quartile 3 X Age group (4)	0.56 (0.39)
Quartile 4 X Age group (2)	0.04 (0.39)
Quartile 4 X Age group (3)	0.40 (0.35)
Quartile 4 X Age group (4)	0.38 (0.45)
Age group (ref: Age group (1) (>=15 to <25 years))	
Age group (2) (>=25 to <35 years)	0.27 (0.32)
Age group (3) (>=35 to <=50 years)	−0.05 (0.29)
Age group (4) (>50 to < 100 years)	−0.06 (0.31)
Controls	*Yes*
Mean obesity	0.35
Pseudo R-squared	0.13
Observations	1,345

Notes: Robust standard errors in parentheses. *** P-value < 0.01, ** P-value < 0.05, * P-value < 0.1. Standard errors are clustered at village level. SPF – semi-processed foods, UPF – ultra-processed foods.
Controls include education, occupation, marital status, number of children, household size, religion, caste, asset quartiles, ration card, share of food purchases from modern retail stores, person buying food from the market, number of household members regularly eating meals away from home, access to safe drinking water, access to toilet, distance to Bangalore city center, and a dummy for research transect.

5.2. *Heterogeneities in the relationship between processed foods and obesity*

Although the share of calories consumed from UPF in our setting is on average small (4.1 percent) compared with the share for SPF (17.9 percent) (see Table 1), the regression results in Table 3 show that higher shares of calories consumed from UPF are associated with an increased prevalence of obesity among women. As we proposed in section 2.1, this relationship might reflect the energy density of UPF and their greater affordability for members of higher SES groups. To further explore this argument, we conduct the following heterogeneity analyses for the relationship between processed foods and obesity.

5.2.1. *Analysis by the socio-economic status of the household*

To explore the relationships among processed foods, SES, and obesity, we test the correlations between processed foods and obesity by quartiles of the household asset index. The results are presented in Table 4. In Table 4, we see that a higher share of calories from SPF is associated with higher prevalence of obesity among women in asset quartile 3. However, it is the share of calories from UPF that is correlated with obesity among women in the highest asset quartile 4. UPF are also associated with the increased prevalence of obesity among women having higher education (Table 5). Women with higher education are likely to have both higher SES and higher opportunity costs of preparing meals, and are thus more likely to display an association between UPF and obesity. One reason for the lack of a significant correlation between UPF and obesity in lower-middle SES households despite the energy-dense nature of UPF could be that absolute levels of UPF consumption are low in these households.

5.2.2. Analysis by the ration card status of the household

Another potential explanation for the differences between lower, middle, and higher SES could be the access to SPF and UPF. A recent study for Karnataka shows that ration card holders rely more on the energy-dense foods purchased at a subsidized price in PDS and on open markets (Cunningham et al., 2021). Table 6 shows how the prevalence of obesity changes in households that hold ration cards as the consumption of processed foods increases. Below poverty line (BPL) ration cardholders, who are entitled to the largest share of benefits from PDS, are at greater risk of obesity due to excess consumption of calories from SPF. The prevalence of obesity among above poverty line (APL) ration cardholders (not poor but food insecure in some cases), who are entitled to a small quantity of subsidized staples by PDS, is not affected by processed food consumption. Both SPF and UPF appear to be associated with a reduction in obesity in non-ration cardholders. A possible explanation is that non-ration cardholders, who typically have higher SES, might be more conscious of the importance of dietary quality, and make consumption choices accordingly (Cunningham et al., 2021).

5.2.3. Analysis by the calorie adequacy status of the household

Overconsumption of calories has been identified as a major risk factor for obesity (Hill et al., 2012). We check whether the relationship between SPF and UPF consumption and obesity depends on whether more or less than the RDA for calories is being consumed. In Table 7, we present the relationship between processed foods and obesity in calorie-adequate and calorie-inadequate households. As expected, we find that excess consumption of SPF calories (quartile 4) is strongly associated with obesity in calorie-adequate households. Consumption of calories from processed foods is not associated with the prevalence of obesity for women in calorie-inadequate households. This suggests that there is a threshold in the form of one's baseline ability to meet their RDA for calories, beyond which excess consumption of SPF is associated with obesity. However, calorie adequacy does not appear to be a threshold in the relationship between UPF and obesity in our sample.

5.2.4. Moderation by the occupational activity of women

Several studies show that individuals engaged in physically strenuous occupations are less likely to be obese (Dang et al., 2019; Mo et al., 2022; Monda et al., 2008). The results for model 3 (Table 8), which includes interaction variables for SPF and UPF with the occupation of women, show that compared to quartile 1, SPF calories at the highest quartile of consumption (4) are associated with increased prevalence of obesity. Furthermore, the association between SPF calories and obesity weakens for women engaged in labor-intensive occupational activities. That is, for women engaged in labor-intensive work such as farming or casual labor, and for students, who might engage in sports and other forms of exercise at their educational institutions, excess consumption of SPF calories appears to be offset by the physical intensity of occupational activity. Neither the UPF calories nor their interaction with the occupation is significantly associated with obesity prevalence in model 3.

5.2.5. Moderation by age group of women

Studies show that older women in India have higher social status within the household as they tend to have higher decision-making power than young women (Agarwal et al., 2021; Kumar et al., 2021). This decision-making power might mediate the relationship between processed foods and obesity among older women in our study setting since they could be the ones deciding the overall diet for the household. It is also possible that due to their age, they may be less physically active. To explore this, we interact age of women with the share of calories from SPF and UPF (model 4). The results of model 4 (Table 9) show that as women get older the association between SPF consumption and obesity becomes stronger. Similar to the results for occupational activity presented above, this suggests that the combination of less physical activity (due their age) and higher consumption of SPF is associated with the increased prevalence of obesity.

5.3. Discussion of potential policy implications

We propose three policy recommendations based on this research. First, interventions like *Poshan Abhiyan* in India focus on several complementary themes such as food fortification, increasing consumption of iron rich food items, dietary diversity, etc. to improve nutritional outcomes among children and women. Together with these, knowledge about the benefits of moderation of SPF and UPF intake is essential to ensure that the health interventions targeting diet are successful in delivering their goal of reducing malnutrition particularly in the dynamic RUI regions and among the poorer populations.

Second, studies show that food safety net programs are associated with increased obesity prevalence (Cawley, 2015). In India too, SPF such as sugar and oil are provided to people at relatively lower prices through PDS. We find that overconsumption of these foods is associated with the increasing prevalence of obesity in our study setting. Thus, refocusing PDS – the largest safety net program in India – from a staple food-oriented approach to include more fresh and unprocessed food items is important to reduce the prevalence of obesity. However, a caveat here is that there are supply-chain challenges associated with delivering and preserving fresh foods, as evidenced for example by the Sembako program in Indonesia (Banerjee et al., 2021; Dewi et al., 2022). Nevertheless, even if delivering fresh foods maybe ambitious given all the problems facing the current PDS system in India (Singh et al., 2021), other ways to encourage people to invest in healthy eating can be achieved by subsidizing healthy food, increasing processed food taxes, and incentivizing companies to invest in culturally-sensitive food labelling. Similar public finance and public health interventions have seen success in reducing obesity in India, Mexico, and Chile (Afshin et al., 2017; Frenk, 2006; Singh et al., 2022; Taillie et al., 2021). What is clear is that pre-emptive action through greater awareness may be key to stemming the spread of the obesity epidemic into lower- and middle-income groups.

Finally, we also show that age and physical intensity of occupational activity moderate the relationship between obesity and SPF. Food and nutrition policy should thus incorporate incentives for exercise. This could include both targeting people with information on the benefits of regular exercise as well as encouraging investments in green public places, city parks, outdoor gyms, and neighborhood safety. Along with the former to create internal motivation to improve health, the latter recommendations would help create an external environment to motivate physical activity.

5.4. Limitations of the study

Several limitations of our study deserve mention. First, we identify significant associations, but we cannot draw conclusions about causality because the link between the consumption of processed foods and obesity might be bidirectional. Furthermore, there might be unobserved factors influencing obesity, such as actual physical activity and lifestyle changes, which are not accounted for in our dataset. We cannot overcome this issue with our cross-sectional survey data. Hence, we propose that our results are to be interpreted as correlational and that more research is needed to further explore these relationships.

Second, since the calories from processed foods in our study are measured at the household level but BMI outcomes are measured at the individual level, our results might be biased by intra-household disparities in food allocation. However, we propose that intra-household nutrient distributions have been found to be equitable in other contexts (Berti, 2012; Coates et al., 2018; Coates et al., 2017), in particular for calories, which is the focus of our study. Additionally, based on the previous studies (Gupta et al., 2020; Harris-Fry et al., 2018) and our experience of conducting field surveys in India, we believe that women are consuming less than the average household member. Hence our results might under-estimate the relationship between obesity and processed food consumption. Nonetheless, we acknowledge that future research exploring the relationship between individual intake of processed foods and obesity will provide more nuanced discussions on the topic analyzed here.

Third, our analysis is based on 14-day recall data on food consumption at the household level. While the 24-hour and weekly recalls are more common in the literature, we focused on the longer-term recall to increase the probability of getting information on less frequent (often monthly) purchases of bulk foods. These foods make important contributions to total calorie consumption of the household. Additionally, to ensure that we captured all possible food consumed, we carefully trained enumerators to probe for information on foods consumed outside the home, for example collecting information on tea/coffee and street foods/snacks consumed by other household members outside the home. However, it is possible that we nevertheless undercount calories from UPF consumed outside the home and that this explains the weaker correlation of obesity with UPF calories among lower-middle SES women. We submit that even if this is the case, we are at worst underestimating the relationship between UPF calories and obesity for lower-middle SES women but that the relationship to SPF calories that we find will continue to hold since our survey accounts for these purchases thoroughly.

Fourth, we have used the occupational activity of women as a proxy for the physically demanding or sedentary nature of their employment. However, we agree that we cannot fully comment on the individual level association between non-occupational physical activity (e.g. sports, leisure, etc.) and the prevalence of obesity without actual data on physical activity. This reduces our ability to rule out the individual level metabolic channel that moderates the relationship between processed food consumption and obesity. Nutrition research is key to generating more detailed insights into this topic, but beyond the scope of our analysis.

6. Conclusions

We analyze the relationship between processed food consumption and obesity in India. Even though prevalence of obesity in India has doubled over the last decade, the literature explaining this phenomenon is only now emerging. We focus on the peri-urban context in India, which is at the greatest risk of the obesity burden (Aiyar et al., 2021b).

Using unique cross-section data from peri-urban areas of Bangalore, a fast-developing city in India, we find three potential correlates that suggest how processed food calories and obesity become inter-linked during the nutrition transition. First, we find that the extent of industrial food processing plays a role in linking the dietary transition to obesity. Even at low levels of UPF consumption, our results show that UPF is correlated with obesity in higher SES groups (households in the highest asset quartile) and highly educated women, as seen in more developed countries. We also find that calories from SPF are associated with the increased prevalence of obesity among women in third quartile of the household asset index and among ration card holders in the RUI of Bangalore. Improvements in economic livelihoods among these groups coupled with the low cost of SPF through the PDS enables households in lower-middle SES groups to purchase and consume large quantities of SPF. At higher income and education levels, the diet correlates of obesity shift to UPF due to the greater affordability of such foods and the higher opportunity costs of preparing meals at home (compared with lower-middle SES groups).

Second, there is a threshold effect in the relationship between processed foods and obesity. Among the women in households that consume less than their RDA of calories, there is no association between the consumption of SPF and obesity. This relationship turns significant only for women in households that meet and exceed their RDA for calories. Thus, the RDA for calories marks a threshold beyond which obesity becomes associated with consumption of SPF.

Third, the relationship between SPF calories and obesity is moderated by a women's levels of physical activity. In line with the broader literature (Dang et al., 2019; Monda et al., 2008), our results show that engaging in relatively labor-intensive occupational activities reduces the strength of the correlation between SPF and obesity. Age also plays a role, as we find that older women are more likely to have a strong correlation between SPF consumption and obesity. The existence of the threshold and the activity relationship implies that both targeting nutrition information on weight management and moderation of calorie consumption along with information on improving exercise routines could contribute to moderating the negative consequences of the nutrition transition in the RUI.

Targeting the poor through appropriate food subsidies can increase social welfare, but at the same time it is important to avoid increases in the prevalence of obesity that often accompany the nutrition transition. Using the PDS to supply healthy diets and fresh foods, combined with taxes on processed foods and re-thinking subsidies for SPF, could reorient markets towards the production and consumption of more healthy diets in the Indian RUI. Given that obesity is now recognized as a public health hazard, and its relationship with increased risks of non-communicable diseases are known, taking preventative action in villages and towns that are at the cusp of the urbanization process in India, may make an important contribution to stemming a public health crisis.

Conflict of Interest and Funding Disclosure

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CRediT authorship contribution statement

Anjali Purushotham: Conceptualization, Data collection, Data curation, Methodology, Formal analysis, Writing – Original Draft, Writing – Review & Editing. **Anaka Aiyar:** Conceptualization, Methodology, Writing – Original Draft, Writing – Review & Editing, Supervision. **Stephan von Cramon-Taubadel:** Conceptualization, Writing – Review & Editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendices.

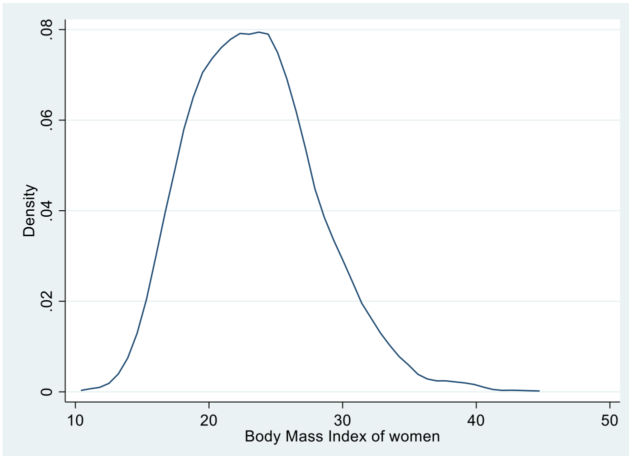

Fig. A1a. Kernel density estimation of body mass index (BMI) among sample women.

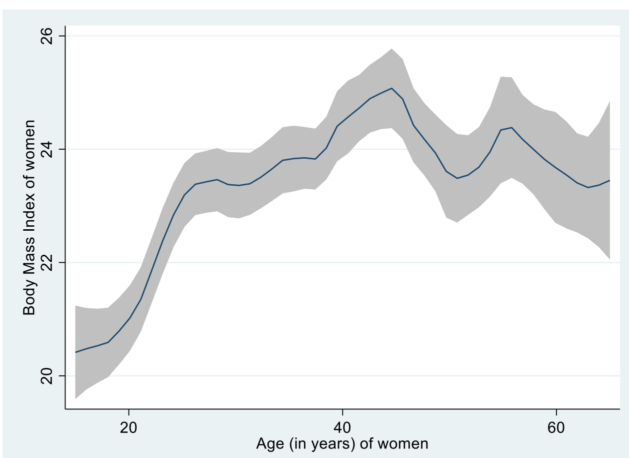

Fig. A1b. Local polynomial estimation of BMI as a function of age (65 years and below). The gray shaded area in the graph represents 95 percent confident intervals.

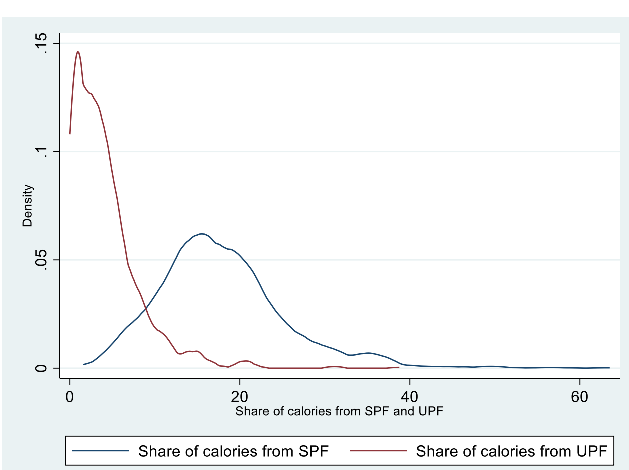

Fig. A2. Kernel density estimation of the share of calories consumed from the semi-processed foods (SPF) and ultra-processed foods (SPF).

Table A1
logit regression to test differences between women with and without BMI information in the sample.

Variables	Women with known body mass index (BMI) information (versus not known)
Age (years)	−0.00 (0.01)
Education (years)	**−0.09*** (0.03)**
Marital status (ref. Married)	
Unmarried	1.36 (1.44)
Divorced/widowed	−0.56 (0.48)
Main occupation (ref. Housewife)	
Office work	−0.36 (0.41)
Labor-intensive work	−0.52 (0.34)
Student	0.32 (1.35)
Others	0.27 (0.67)
Number of children (count)	0.03 (0.10)
Household members (count)	**−0.11** (0.05)**
Religion (dummy - Hindu)	0.34 (0.37)
Caste (ref. General)	
Schedule caste & schedule tribe (SC&ST)	**0.49* (0.28)**
Other backward castes (OBC)	0.34 (0.35)
Assets (count) (ref. Quartile 1)	
Quartile 2	−0.58 (0.40)
Quartile 3	−0.13 (0.35)
Quartile 4	0.11 (0.51)
Ration card (ref. No ration card)	
Above poverty line (APL) ration card	0.17 (0.57)
Below poverty line (BPL) ration card	0.36 (0.33)
Grocery purchase from modern food outlets (%)	0.00 (0.01)
Main grocery shopper (ref. Adult female)	
Adult male	0.14 (0.29)
Anybody in the family	0.22 (0.45)
Meals away from home (MAFH) (count)	−0.06 (0.22)
Safe drinking water (dummy - yes)	**0.92* (0.48)**
Toilet (dummy - yes)	0.32 (0.79)
Distance to Bangalore (km)	0.01 (0.02)
Location (dummy - North)	−0.05 (0.29)
Pseudo R-squared	0.06
Observations	1,413

Note: Robust standard errors in parentheses. *** P-value < 0.01, ** P-value < 0.05, * P-value < 0.1. Standard errors are clustered at village level.

Table A2
t-test for women with and without missing covariates.

Variable	Testing mean differences	
	BMI for missing covariate	BMI for non-missing covariate
Occupation	23.43	23.43
Caste	25.07	23.42
Toilet	24.18	23.41
Person buying food	22.47	23.43

Notes: *** significant at P-value < 0.01, ** significant at P-value < 0.05, * significant at P-value < 0.1. BMI – body mass index.

Table A3
Summary of food items classified under 3 food groups of NOVA classification system.

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

Table A4
Socio-economic correlates of semi- and ultra-processed food consumption among women in the rural–urban interface – OLS regression.

Variables	Share of calories from semi-processed foods (SPF) (%)	Share of calories from ultra-processed foods (UPF) (%)
Age (years)	0.01 (0.02)	**−0.02* (0.01)**
Education (years)	**0.13** (0.06)**	0.04 (0.03)
Marital status (ref. Married)		
Unmarried	−1.09 (0.99)	−0.69 (0.87)
Divorced/widowed	0.88 (1.04)	0.38 (0.45)
Main occupation (ref. Housewife)		
Office work	0.42 (0.70)	0.07 (0.37)
Labor-intensive work	0.24 (0.57)	−0.18 (0.30)
Student	**2.17* (1.22)**	−0.23 (0.91)
Others	−0.64 (0.91)	0.23 (0.53)
Household members (count)	0.00 (0.13)	0.02 (0.06)
Religion (dummy - Hindu)	**−3.27*** (1.22)**	−0.62 (0.65)
Caste (ref. General)		
Schedule caste and schedule tribe (SC & ST)	**−1.25* (0.66)**	0.52 (0.42)
Other backward castes (OBC)	0.14 (0.81)	−0.05 (0.37)
Assets (count) (ref. Quartile 1)		
Quartile 2	0.38 (0.69)	−0.06 (0.33)
Quartile 3	0.17 (0.85)	0.50 (0.42)
Quartile 4	**2.19*** (0.76)**	−0.49 (0.47)
Ration card (ref. No ration card)		
Above poverty line (APL) ration card	−0.23 (1.39)	−0.63 (0.77)
Below poverty line (BPL) ration card	**−2.65*** (0.84)**	**−1.06** (0.49)**
Grocery purchase from modern food outlets (%)	0.01 (0.01)	0.01 (0.01)
Main grocery shopper (ref. Adult female)		
Adult male	0.28 (0.71)	0.06 (0.38)
Anybody in the family	0.70 (0.76)	0.52 (0.38)
Meals away from home (MAFH) (count)	−0.21 (0.33)	**0.70*** (0.20)**
Distance to Bangalore (km)	**−0.07** (0.03)**	**−0.07*** (0.02)**
Transect (dummy - North)	−0.27 (0.83)	0.11 (0.35)
R-squared	0.1	0.09
Observations	1345	1,345

Notes: Robust standard errors in parentheses. *** significant at P-value < 0.01, ** significant at P-value < 0.05, * significant at P-value < 0.1. Standard errors are clustered at the village level.

The summary of these regression results show that food consumption patterns are related to income and distance. Higher income and higher socio-economic status (SES) groups consume more of semi-processed foods (SPF) than the lower SES groups – measured by income, higher education, general caste category, and ownership of below poverty line (BPL) cards. Whereas younger women and women in household where more household members consume meals away from home (MAFH) are found be consuming higher share of calories from ultra-processed foods (UPF). The further one is away from Bangalore, the lower they report having consumed SPF and UPF foods, indicating the role of access to food in determining consumption. These results align with the idea that there is an income effect associated with the consumption of processed foods which is moderated by access to such foods.

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