Food Subsidies and Substitution: Experimental Evidence Using Objective Food Purchase Data

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Abstract

In this paper we examine the effects of in-kind food subsidies on the food purchasing patterns of low-income individuals in India, using objective scanner data. We digitally tracked the purchase histories of over 20,000 individuals by installing scanners in 39 food-selling vendors including groceries, butchers, and street food sellers, in an urban settlement in India. We document heavy consumption of packaged junk foods. In groceries, the share of calories coming from the purchase of packaged snacks (e.g., chips or candy) exceeds that from the purchase of rice and wheat combined. To study how food subsidies impact food shopping and in turn nutrient purchases, we opened a store that mimicks the Indian government's food subsidy stores, and randomly assigned 1,258 individuals to a weekly rice and wheat subsidy treatment arm or to a no-subsidy control arm, for a 6-week period. Participants' shopping patterns indicate a substitution from snacking out towards home-cooked meals. The purchase of packaged snacks decreases, whereas that of complementary foods – such as spices and accompaniments – increases – with no detectable change in total grocery spending or spending at other tracked food vendors. These effects are most prominent for working parents. We find no evidence of a negative spillover on the purchase of calories, carbohydrates, protein, fat, and several micronutrients, which suggests that nutrients delivered through an in-kind food subsidy program are likely to stay with the beneficiaries.

"The desire of food is limited in every man by the narrow capacity of the human stomach."

Adam Smith

What is the nutritional impact of in-kind food subsidies targeted to the poor? In this paper, we propose new and objective data sources, experimental evidence, and methodology to study this question. Every year, malnutrition is estimated to cause 3.5 trillion dollars worth of economic loss (Swinburn et al., 2019), and it is the cause of nearly half of all child deaths.[1] As a response, governments and aid organizations inject billions of dollars into their food programs.[2] For

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[1]https://www.who.int/health-topics/malnutrition

[2]The World Food Program won the 2020 Nobel Peace Prize, exemplifying the scale and policy centrality of food programs in addressing malnutrition in base-of-the-pyramid markets. In the developed world, for instance, the United States government spent 111 billion dollars on domestic food assistance in 2021. Available at here https://www.cbpp.org/research/food-assistance/the-supplemental-nutrition-assistance-program-snap

instance, government food subsidies account for 2 percent of Egypt's GDP – or about half of its healthcare expenditure.[3] Therefore, estimating the impact of food subsidies is an issue of major social and economic significance to policymakers.

Food subsidies are government-led policy interventions that make nutritious foods available and accessible to low-income populations. Albeit with similar nutritional objectives, these programs take several forms – ranging from food vouchers that can be redeemed in food-selling vendors such as groceries (Banerjee et al., 2023) to in-kind food subsidies that directly provide the food or direct cash transfer (Cunha, De Giorgi and Jayachandran, 2019). This paper focuses on in-kind food subsidy programs, which are widely adopted in developing countries (Alderman, Gentilini and Yemtsov, 2017). In these programs, governments often establish a supply chain network, set up store fronts, and distribute rationed quantities of subsidized food to targeted beneficiaries. An example is India's nationwide Public Distribution System (PDS). This program offers monthly cereal subsidies to nearly 800 million individuals living below the poverty line through 500,000 subsidy stores, known as 'fair price shops'.[4]

Despite their policy centrality, there is little or no consensus on whether food subsidies improve nutrition (Stifel and Alderman, 2006; Jensen and Miller, 2011; Svedberg, 2012; Kaushal and Muchomba, 2015; Colen et al., 2018; Shrinivas et al., 2018). In fact, Jensen and Miller (2008) show that the staple food subsidies exhibit a Giffen good behavior. However, there are several empirical challenges in evaluating the impact of food subsidy programs in low-income markets. First, such programs have often been in place for many decades at a country level, rarely changing in their structure. Therefore, the available data often lack the temporal or geographic variation needed to identify the impact of food subsidies.[5]

Another barrier to estimating the impact of food subsidies is that objective data describing food consumption is virtually unavailable in developing economies.[6] Research to date relies heavily on self-reported dietary recall measures, often collected via national nutrition surveys. In such surveys, respondents are asked a battery of questions to infer their food consumption

[3] Available at https://openknowledge.worldbank.org/handle/10986/2913 and at https://data.worldbank.org/indicator/SH.XPD.CHEX.GD.ZS?locations=EG

[4] Available at https://nfsa.gov.in/public/nfsadashboard/PublicRCDashboard.aspx

[5] Some exceptions are experiments conducted at scale in collaboration with governments, e.g., those run by Banerjee et al. (2021) in Indonesia, or Jensen and Miller (2008) in China. In the context of India, several studies use quasi-experimental variation induced by policy changes such as targeting (Kochar, 2005) or introducing the national food security act (Shrinivas et al., 2018).

[6] There are notable exceptions that objectively measure the consumption of a particular product category. Schilbach (2019) studies the impact of a commitment device to reduce daytime drinking and measure alcohol consumption via breathalyzers. Banerjee, Barnhardt and Duflo (2018) collect blood samples to objectively measure the effects of promoting iron-fortified salts on hemoglobin levels.

on an average day or month preceding the survey date. There are three main shortcomings to this type of self-reported data. First, because survey questions measure consumption at the product category level, it is notoriously difficult to track the consumption of consumer packaged goods. For example, India's widely used National Sample Survey Organization nutrition survey, which includes 659 questions, contains only one question that asks about biscuits and candy.[7] Related to this issue, Deaton and Drèze (2009) highlight that little is known about the junk food consumption of impoverished individuals. Second, subjective reports are liable to recall bias and misreporting – possibly due to social desirability bias. Third, despite being representative, national surveys collect repeated cross-sectional data, which do not allow for tracking of within-individual variation in outcomes over time.[8] Even if there is exogenous variation in access to subsidies across individuals in a cross-section, if the effect of the subsidy on outcomes of interest is small relative to variation across individuals in these outcomes, the subsidy effect would be hard to detect in the absence of within-individual variation over time.

In this paper, we propose an experimental approach to generate exogenous variation in access to food subsidies by mimicking government food subsidy programs. In essence, we set-up and implement an in-kind food program that imitates the fair price shops (i.e., subsidy stores) of the Indian PDS. We did so by opening our own "subsidy store" in Mankhurd, the poorest urban settlement in Mumbai, India (HDR, 2010), to disburse government-like subsidies. We recruited a sample of 1,258 low-income individuals into our experiment and randomly assigned participants to either a weekly food subsidy treatment offered over a 6-week period or to a control arm. Between July 1^{st} and September 4^{th} of 2022, we distributed over 11 tonnes of cereal (specifically, rice and wheat) food subsidies through our program.

Moreover, to circumvent the shortcomings of self-reported data collection and to gather multiple observations on individuals over time both before and during our subsidy intervention, we purchased scanner devices, as well as smartphones operated with (equipped with) a retail point of sale (POS) app. We equipped 39 food-selling vendors – ranging from groceries and butchers to street food sellers – with these technologies and deployed research assistants to record transactions, in the same community in which we offered our food subsidy program. Finally, we ran an incentive program with the customers of our partner stores, through which

[7] Available at https://catalog.ihsn.org/index.php/catalog/3281

[8] Some studies repeatedly collect a detailed 24-hour dietary recall questionnaire on the same sample, to construct panel data (e.g., see Rajagopalan et al. 2021 in the Indian context). These surveys are more onerous to collect, often limited by the sample size or panel length.

we "tagged" each bill with a unique customer identifier. Tracking individual customers across their shopping instances enabled us to construct a panel dataset of food purchases. During the experimental period, we recorded over 700,000 transactions and tracked over 20,000 low-income settlement dwellers across our partner stores. Furthermore, we mapped each SKU purchased to its nutritional content.[9] To the best of our knowledge, this data enables the first objective measurement of food shopping in a low-income market at SKU-level granularity. We use these data to understand food shopping patterns and to identify the effects of our food subsidy program on food shopping behaviors and on the associated purchase of nutrients.

We uncover three key findings. First, we document a striking amount of junk food consumption. Absent food subsidies, respondents purchase more calories from packaged snacks (defined as chips, chocolates, biscuits, ice cream, and candy) than from rice and wheat combined. Second, random assignment to the food subsidy induces a substitution from "snacking out" to eating at home. We show that respondents who receive our food subsidies are significantly less likely to buy snacks, soft drinks, or nuts. At the same time, they significantly increase their purchases of supplementary food such as spices and accompaniments, although there are no significant changes in the total amount spent on groceries or in other food vendors that we track, both overall and across several subsample analyses. Third, nutritionally, we find no negative spillovers. Individuals in both trial arms purchase similar amounts of calories, carbohydrates, protein, fat, and several micronutrients in our partner stores, both overall and across the subsample analyses. These findings suggest that the nutrients delivered through our food subsidy program are likely to have stayed with the beneficiaries.

In our sample, parents buy significantly more snacks than non-parents, and the majority of them report junk food as the top product category that their children purchase in groceries. When we split the sample by parental status, we find that the negative treatment effect on snack purchases is stronger for parents. The greater amount of junk food purchased by parents and the stronger negative treatment effect on junk foods for parents highlight the value of food subsidies for children's long-term development – which has long been linked to nourishment (Britto et al., 2017). Furthermore, we find that the drop in snack purchases by parents is coming from the employed sample.[10] These effects may reflect the burden on employed parents of childcare obligations.

[9]We recorded the nutrition table printed on each product's package or used other sources, such as Indian Food Composition Table, for loose items. see Online Appendix Section A.B.

[10]This effect holds both without and with a control for the participant's gender.

1 Food purchasing habits in an urban settlement in India

Little is known about the food shopping patterns of the poor in developing countries, particularly their consumption of junk food (Deaton and Drèze, 2009). As a first step towards systematic documentation of food purchases in a low-income community, we implemented a large-scale scanner data collection process in a relatively isolated area in Mankhurd, Mumbai (see Online Appendix Figure A.1 for the Geomap). In the three streets and one cross-alley that comprised our selected neighborhood, we approached all 52 food (or tobacco) selling vendors and invited them to participate in our study. We gradually enrolled 39 stores, and started recording their transactions before the start of our experiment.[11] Although our main focus is on groceries, we also partnered with other store types that operate in our chosen neighborhood, specifically, both of the two butchers, both of the two street food vendors, one of the two dairy stores, one fruit and one vegetable seller out of four, and two of the five corner shops (these shops mostly sell tobacco products) that operate in our chosen neighborhood. By equipping each store with a scanner device and deploying a full-time research assistant (RA) at each of these stores, we digitally record nearly all the transactions that occurs during the data collection period. We validate the exhaustiveness and quality of the data via mystery shoppers (undercover enumerators, whom we ask to purchase a pre-determined shopping basket that enabled cross-checking for data accuracy).[12] Our scanner data includes the participant's study ID (a unique identifier for each individual), the list of products purchased in each shopping instance, their prices, quantities, a timestamp, and a unique identifier for each shopping instance.[13] For each line item, we determine its corresponding product category and macro and micronutrient composition.[14]

Between March and October 2022, we recorded 777,980 product transactions made by 23,719 unique customers. Across our 39 partner stores, we tagged 84.05 percent of all transactions with

[11] We installed our first device on March 10, 2022 and gradually expanded our store network until June 15, 2022

[12] We took additional steps to make the transaction recording protocol incentive compatible by providing monetary incentives to RAs and store owners. See Online Appendix Section A.A and Table A.2 for more details.

[13] To identify each customer we "tag" the shopping bill with the customer's name and phone number. To encourage customers to disclose this information, we run an incentive program. At the end of the experiment, we conduct a lottery event where we distribute prizes to randomly selected individuals in our pool of identified customers. In practice, customer tagging is semi-automated and becomes efficient time-wise in subsequent transactions, as the RA recognizes the regular customers, and identifies their details from the previously saved list of customers. For shopping instances where we are unable to tag the bill with customer details, we nevertheless record the transaction details.

[14] Note that as our focus is on nutrition, we label all non-food items under one category. The only exception is tobacco products, which we include in the scope of our study given their adverse consequences for health. See Online Appendix Section A.B for the details of product-nutrient mapping.

a unique customer identifier.[15] On average, we observe each customer in 23.8 different shopping instances and in 2.2 different stores. The median time elapsed between two consecutive shopping instances of a tagged customer in our sample is 21.5 hours.[16]

Table 1 presents descriptive statistics regarding the food purchasing patterns of individuals in our partner grocery stores. To eliminate occasional shoppers, we restrict our analysis to those for which we observe on at least 3 different grocery food shopping instances. Furthermore, we drop individuals who were enrolled in the experiment (or pilot studies) to avoid the effects of the subsidy on the treatment arm – or of the post-experiment subsidies on the control arm. This leaves us with a sample 8,789 individuals. Three notable patterns emerge.

The urbanization of poor populations expands their access to previously less accessible junk foods (Clark et al., 2020). At 21.4 percent of expenses in groceries, packaged snacks (i.e., chips, chocolates, biscuits, ice cream, and candy) are the highest source of calorie purchases in groceries, in our sample. In our sample, 13.9 percent of an average individual's expenditure went into snacks. This amount is greater than the amount they spend on rice and wheat combined (10.31 percent), and it also exceeds the amount spent on any other category of grains or legumes.

Increased junk food consumption among adolescents is a well-known global public health challenge. In developing countries, it is often imbued with social status and goes hand in hand with a reduction in the consumption of home-cooked meals (Neufeld et al., 2021). In our baseline survey, 74 percent of low-income parents reported junk food as the top category of food products purchased by their children. Despite economic development, child malnutrition rates in India are higher than in sub-Saharan African countries, on several key metrics.[17] More recent data also suggests that the Indian child's malnourishment is worsening (Chatterjee, 2021). As snacks, such as chips and chocolates, have high calories but lack protein or micronutrients, heavy consumption of these products could be contributing to the child malnutrition challenge in India.[18]

We find suggestive evidence corroborating this argument. In our experimental sample, there

[15]Untagged bills include those of customers who did not consent to share their details as well as those of members of the vulnerable population including underage individuals and people with learning or communication disabilities.

[16]Note that to calculate inter-shopping time, we only use data from 12,555 tagged customers who we observe on at least three distinct shopping instances.

[17]This phenomenon is known as the South Asian Enigma. Details at https://www.ifpri.org/blog/unraveling-enigma-south-asian-malnutrition.

[18]India ranks 120th among 128 countries in the global hunger index for children. A major contributor to this is micronutrient deficiency – also known as hidden hunger. Available at https://ebrary.ifpri.org/utils/getfile/collection/p15738coll2/id/128360/filename/128571.pdf

is an economically sizeable and statistically significant correlation between having children and snack purchases, but not other purchases such as rice or spices.[19] Parents purchased about fifty percent more snacks compared to childless adults—an amount that equates to the (linear) effect of having eight additional members in the household.

Table 1: Customers' Share of Grocery Food Expenditure Across Product Categories

	Spending (%) (1)	Count (%) (2)	Calories (%) (3)	Carbohydrates (%) (4)	Protein (%) (5)	Fat (%) (6)
Rice	6.465	3.418	9.373	12.978	9.714	1.598
	(14.065)	(7.353)	(19.379)	(24.653)	(20.070)	(7.102)
Wheat	3.851	1.782	5.666	7.679	7.082	2.217
	(11.323)	(5.707)	(5.666)	(7.679)	(7.082)	(2.217)
Legumes	7.759	5.345	5.885	8.527	14.098	1.656
	(13.954)	(9.407)	(12.863)	(17.396)	(23.219)	(7.398)
Other grains	7.786	9.369	15.429	15.936	13.465	11.233
	(12.228)	(11.980)	(26.904)	(25.259)	(22.240)	(23.241)
Spices	7.254	11.853	5.948	6.914	7.868	7.504
	(14.409)	(16.659)	(15.305)	(17.442)	(18.259)	(18.383)
Accompaniments	0.194	0.293	0.125	0.191	0.035	0.067
	(2.154)	(1.960)	(1.832)	(2.570)	(0.727)	(1.517)
Snacks	13.963	21.806	21.365	27.617	13.402	19.726
	(17.747)	(19.892)	(26.517)	(30.190)	(23.350)	(28.148)
Ready to eat	0.245	0.324	0.160	0.156	0.258	0.032
	(2.234)	(1.965)	(2.705)	(2.423)	(3.224)	(1.025)
Nuts	0.745	0.576	0.422	0.341	0.565	0.801
	(5.080)	(3.302)	(3.723)	(3.515)	(4.480)	(5.952)
Soft drinks	5.582	6.323	2.914	3.845	0.323	0.269
	(13.491)	(12.862)	(11.211)	(13.123)	(4.073)	(3.766)
Dairy	25.133	22.395	18.312	13.904	26.504	26.301
	(28.860)	(24.846)	(28.021)	(24.779)	(32.614)	(33.925)
Eggs	3.787	3.385	1.698	0.098	4.153	3.056
	(10.038)	(8.023)	(7.268)	(2.112)	(12.621)	(10.810)
Cooking oils	10.540	4.805	11.245	0.437	0.363	25.056
	(18.269)	(9.187)	(20.175)	(4.333)	(3.860)	(36.313)
Other foods	2.550	3.309	1.457	1.377	2.171	0.483
	(7.159)	(6.503)	(6.917)	(6.548)	(8.664)	(4.303)
Tobacco	4.146	5.016				
	(15.381)	(16.120)				

Notes: This table presents descriptive statistics on the average customer's share of food (and tobacco) sources in groceries across several metrics. The sample in this table consists of 8,789 individuals (after removing occasional shoppers and the experiment sample). Columns 1 presents the average of the percentage of food expenditure during our sample duration coming from each product category. Column 2 presents similar statistics for the average share of distinct SKUs purchased. Columns 3 to 6 present the average share of calories and macro nutrients purchased during our sample duration coming from each product category.

Next, we examine the correlations between purchases of different product categories in the same hour across all our partner food-selling vendors (see Online Appendix Figure A.2). Not surprisingly, we find that staple foods and their accompaniments tend to be purchased together. For instance, rice purchases have higher correlation with legumes, cooking oils, and spices than with any other product category. Purchases of dairy products are negatively correlated with

[19]These correlational results are robust for controlling key demographics including family size and age, as well as purchases in other categories. See Online Appendix Table A.3.

purchases of street food (e.g., samosas), tobacco products, and cold drinks (e.g., carbonated soft drinks). Lastly, in almost a quarter of the instances when a street food purchase occurs, the same customer purchases tea or coffee in the next hour.

2 Measuring the Effects of Government-like Food Subsidies

2.A Experimental design and sample

We pre-registered our study on the AEA RCT registry platform.[20] To facilitate replication, we provide the full study protocol in the Online Appendix Section A.A. This experiment has three building blocks. First, we provide food subsidies to randomly selected individuals. Second, we track participants' shopping baskets before, during, and after the subsidy period. Third, we conduct baseline and endline surveys.

Recruitment, baseline survey. In July 2022, we recruited a sample of 1,258 individuals into our experiment. To eliminate occasional or inactive shoppers, we invited a random subset of customers whose first shopping instance was at least 5 weeks prior to the invitation date, and whose last shopping instance was at most 2 weeks prior to it (see Online Appendix Table A.7 for the enrollment details). At the baseline, we recorded demographics, household information, and a battery of questions about food shopping habits, consumption frequency, food insecurity, as well as food and non-food expenditure. Throughout the experiment, we tracked customers' shopping baskets across our partner stores.

In-kind food subsidy treatment. We randomly assigned each respondent to our in-kind food subsidy program with 40 percent probability or to a no subsidy benchmark with 60 percent probability. Each treatment arm respondent was offered weekly subsidies of 2 kgs rice and 2.5 kgs wheat for a 6-week period.[21] To mimic the delivery method of PDS stores, we rented an office in Mankhurd in a central location that is in close proximity to our partner stores, and we distributed the subsidies through this office. If the subsidy was not redeemed in a given week, the corresponding food quantity could not be rolled over to the following week. To digitally record the transactions in the subsidy store and to track the eligibility status of the treatment arm respondents, we used a relational database that we constructed for this purpose (see Online Appendix Figure A.5).

[20] Details of our pre-analysis plan can be found using registry id AEARCTR-0009615.

[21] During the baseline survey, eligible households received a printed coupon that describes the subsidy program. The food could be collected simply by turning up to the Mankhurd office with this coupon (or their unique respondent ID).

Endline surveys and post-experiment subsidies. During the last two weeks of a respondent experimental period, we administered an endline survey. To maintain fairness across the trial arms, control arm participants also received a subsidy. Two weeks after the control arm participants' 6-week experimental period ended, we invited them into a 4-week subsidy program, in which we randomized individuals into four arms to receive a single subsidized product: rice, wheat, lentils or millet.

Sample. Table 2 presents the sample composition. The median respondent is 33 years old, living on 3,500 Indian Rupees a month – about 1.5 US$ a day. Two-thirds of our sample are interstate migrants, mostly from Bihar and Uttar Pradesh, and half are unemployed or daily-wage workers. Strikingly, almost one in every ten households had a member who had tuberculosis in the year before the baseline. Consistent with previous studies (Banerjee and Duflo, 2008), a large share of the household income (62 percent) is spent on food.

Table 2: Sample Composition

	Mean	Standard deviation	Median	95^{th} Percentile	5^{th} Percentile
Age	32.67	10.02	33.00	53.00	22.00
Female	0.35	0.48	0.00	1.00	0.00
Any high school (or higher) education	0.33	0.47	0.00	1.00	0.00
Employed	0.63	0.48	1.00	1.00	0.00
Daily wage worker	0.15	0.36	0.00	1.00	0.00
Self-employed	0.12	0.33	0.00	1.00	0.00
Married	0.75	0.43	1.00	1.00	0.00
Number of household members	4.90	1.96	5.00	8.00	2.00
Any Children Under 9	0.47	0.50	0.00	1.00	0.00
Monthly income per household member (Rs.)	4,257	3,321	3,500	10,000	1,500
Share of household income spent on food	0.62	0.48	0.52	1.45	0.19
Weekly household rice purchase (Kg)	7.72	3.51	6.25	12.50	2.75
Weekly household wheat purchase (Kg)	7.76	3.48	6.25	12.50	2.75
Receive food subsidy	0.50	0.50	1.00	1.00	0.00
Interstate migrant	0.66	0.47	1.00	1.00	0.00
Had Tuberculosis in the family in the last year	0.08	0.266	0.00	1.00	0.00

Notes: Survey responses from 1,258 individuals in Mankhurd, India, in July, 2022.

2.B Estimation

We estimate the intent-to-treat (ITT) effect of random allocation to the food subsidy treatment. Our unit of analysis is a person-week and our estimation takes the following form:

$$Y_{it} = \beta TREAT_{it} + \delta_i + \gamma_t + \varepsilon_{it} \quad , \tag{1}$$

where Y_{it} denotes the outcome variable for individual i in week t, δ_i is a vector of dummies for individual fixed effects, and γ_t is a vector of binaries indicating week-in-panel fixed effects. $TREAT_{it}$ is a binary variable indicating that individual i is on the subsidy treatment arm and week t is a part of the treatment period. Standard errors are clustered by individual, which is our unit of randomization. The coefficient of interest, β, estimates the average impact of the food subsidy treatment on the treatment arm relative to that on the control arm.

The ITT estimates described above reflect the causal effect of *providing access* to a food subsidy program. We are also interested in the effects of eligible individuals actual *take-up* of their subsidies. To do so, we estimate the local average treatment effect (LATE) of subsidy take-up (Imbens and Angrist, 1994). In the first stage, we regress the binary variable indicating subsidy take-up on random assignment to the treatment. Next, in the second stage, we estimate the following regression:

$$Y_{it} = \theta Take\text{-}up_{it} + \sigma_i + \omega_t + \xi_{it} \quad , \tag{2}$$

where $Take\text{-}up_{it}$ is predicted using the first-stage. The estimate θ provides a causal estimate for the impact of taking up of the food subsidies among compliers (i.e., those who take up their subsidies, when offered, and do not, when they are not offered a subsidy). To account for multiple hypothesis testing, in the main regressions we also present the False Discovery Rates sharpened q values, as described in Anderson (2008).

2.C Substitution and complementarity effects

Regression estimates in Table 3 show sizable and significant relative changes in the treatment arm respondents' grocery food expenditure patterns across a variety of measures. Subsidy treatment arm respondents' weekly rice purchases decreased by 0.245 US$ at PPP – i.e., more than 35 percent drop in the treatment arm relative to the control arm mean. Although the treatment food subsidies include wheat alongside rice, we find no statistically significant changes in wheat purchases in the treatment arm during the intervention period, relative to the control arm. This may suggest that different foods may be associated with distinct intra-product substitution effects. Moreover, we find no significant change in the purchases of legumes (e.g., lentils) and other grains (e.g., millets).

Our results are consistent with the hypothesis that food subsidies induce a substitution from snacking out towards home-cooked meals. Treatment arm respondents increase their spices purchases by 0.1 US$ per week (Column 4), which constitutes about 30 percent increase relative to control arm mean. Similarly, there is a significant increase in weekly accompaniments (e.g., chutney, pickles, or ketchup) purchases by 0.013 US$. Spices and accompaniments are rarely consumed alone. Instead, they are used as a seasoning or complement to a home-cooked dish, indicating a potential increase in eating at home.

We find a drop in the purchases of packaged junk foods. Treatment arm respondents face a relative drop in snacks purchases (e.g., chips and chocolates) of 0.074 $US – about 19 percent – relative to no subsidy benchmark. We find statistically significant drops in other categories such as nuts (0.067 $US), soft drinks (0.071 $US–e.g., carbonated drinks or juices), and a mild drop in ready-to-eat food (e.g., instant noodles). These findings are consistent with a pattern of substitution towards home-cooked meals. Naturally, we cannot rule out other potential mechanisms explaining similar co-variations of food purchases. For example, the observed substitution effects may be related to changes in taste preferences.[22]

We next investigate the effects of our food subsidy treatments on purchases from other food-selling vendors such as dairy shops, butchers, fruit and vegetable sellers, and street food vendors as well as corner shops which mainly sell tobacco products. Across these measures, we find no statistically significant effects of food subsidies on purchasing patterns.[23] Finally, we find no significant changes in dietary diversity (measured as the unique number of food products – or categories – purchased) or the total quantity of food (grams) and drinks (milliliters) purchased. These results are presented in the Online Appendix Tables A.8 and A.9.

2.D Heterogeneous effects by family, income, and past shopping behavior

Table 4, Panel A presents separate estimates for samples of individuals with no child and with at least one child. We observe a significant drop in rice and snacks purchases for parents in the subsidy treatment arm relative to the control arm. By contrast, among individuals with no child, we find no significant changes. Both samples increased their spices purchases, but with a more significant increase in the childless individuals. The difference between the trial arms with children for weekly snacks purchases is 0.095 US$ at PPP, or around 20 percent relative

[22]Note, however, that our heterogeneity analyses in the next subsection further suggest that substitution towards home cooking is a factor at play.

[23]Note that individuals are more likely to travel outside our coverage area for meat, street food, and fruit and vegetable purchases. For instance, there is a weekly held fruit and vegetable market in a community nearby. Therefore, the point estimates are scaled down more heavily in these categories relative to other product categories. With that said, it is important to note that, since the treatment assignment is randomized, the intensity at which we track individuals is similar in both trial arms.

Table 3: Effect of Food Subsidies on Grocery Expenditure

	Rice	Wheat	Legumes and other grains	Spices	Accompaniments	Snacks	Ready to eat	Nuts	Soft Drinks
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ITT	-0.245***	0.013	0.062	0.109***	0.013***	-0.074**	-0.007*	-0.067**	-0.071**
	(0.091)	(0.052)	(0.125)	(0.042)	(0.003)	(0.037)	(0.004)	(0.027)	(0.033)
LATE	-0.299***	0.015	0.075	0.133***	0.015***	-0.090**	-0.009*	-0.082**	-0.086**
	(0.111)	(0.063)	(0.152)	(0.051)	(0.004)	(0.045)	(0.005)	(0.033)	(0.040)
Sharpened-q	0.037	0.22	0.184	0.037	0.038	0.047	0.058	0.037	0.038
Control Mean	0.672	0.273	1.266	0.337	0.006	0.409	0.009	0.08	0.179
[Std dev]	[3.643]	[1.659]	[6.104]	[1.228]	[0.124]	[1.207]	[0.163]	[1.018]	[0.81]
Observations	22,236	22,236	22,236	22,236	22,236	22,236	22,236	22,236	22,236

Notes: This table presents the main estimates for weekly food expenditure on groceries. Outcomes are at the person-week level and reported here in levels (US$ PPP). ITT row reports the intention-to-treat (equation 1) and LATE row reports the local average treatment effect (equation 2) estimates, respectively. Both regressions include individual and week-in-panel fixed effects. Standard errors are clustered at the individual level. Last row reports the sharpened-q values for multiple hypotheses correction. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

to the control arm mean. Meanwhile, childless individuals in the treatment arm experienced an insignificant drop in snacks expenditure relative to those in the control arm.

Next, we focus on parents and split the sample by their employment status (see Online Appendix Table A.22). We find that the significant drop observed in snacks purchases among parents is coming from the employed sample (0.143 US$ at PPP — 34 percent relative to the control arm mean), despite the fact that they buy less snacks than unemployed parents in the absence of subsidies. We consider the possibility that the higher rates of men's employment could explain these results for working parents. However, the estimates remain significant with respect to snack purchases after we expand our models to control for the differential impact of food subsidies by gender. Furthermore, we find a significant drop in rice purchases among unemployed parents (0.627 US$ at PPP), whereas employed parents experienced an insignificant decrease (0.092 US$ at PPP). Both the effects of reduced snacks purchases and the fact that they did not substitute away from purchasing rice suggest that employed parents might benefit more from food subsidies. Although the scanner data do not permit investigation of intrahousehold food distribution, these results provide suggestive evidence that having received food subsidies, working parents might divert the children's food consumption away from unhealthy snacks.

We next split our sample by household income, to test whether the effects are stronger for individuals who are less financially constrained, and afford foods beyond their essential needs. Consistent with this prediction, our estimates for rice, snacks, and spices are smaller

Table 4: Effect of Food Subsidies by Parental Status and Household Income and Past Purchases

	No Children			One Child or More		
Panel A. Parental Status	Rice	Snacks	Spices	Rice	Snacks	Spices
	(1)	(2)	(3)	(4)	(5)	(6)
ITT	-0.125	-0.020	0.155**	-0.292***	-0.095**	0.089*
	(0.167)	(0.047)	(0.074)	(0.108)	(0.048)	(0.051)
Control Mean	0.596	0.256	0.301	0.701	0.469	0.350
Observations	6,357	6,357	6,357	15,879	15,879	15,879
Panel B. Household Income	Below Median Income			Above Median Income		
	Rice	Snacks	Spices	Rice	Snacks	Spices
	(1)	(2)	(3)	(4)	(5)	(6)
ITT	-0.168	0.013	0.045	-0.307**	-0.158***	0.170**
	(0.107)	(0.042)	(0.046)	(0.147)	(0.059)	(0.068)
Control Mean	0.623	0.363	0.323	0.726	0.459	0.352
Observations	11,033	11,033	11,033	11,203	11,203	11,203
Panel C. Past Purchasing Behavior	No Purchase			At Least One Purchase		
	Rice	Snacks	Spices	Rice	Snacks	Spices
	(1)	(2)	(3)	(4)	(5)	(6)
ITT	-0.055	-0.009	-0.009	-0.589***	-0.087**	0.156***
	(0.035)	(0.020)	(0.013)	(0.197)	(0.044)	(0.059)
Control Mean	0.047	0.021	0.02	1.31	0.495	0.45
Observations	11,828	3,948	6,189	10,408	18,288	16,046

Notes: Outcomes are at the person-week level and reported here in levels (US$ PPP). All regressions include individual and week-in-panel fixed effects. ITT reports the intent-to-treat estimates. Standard errors are clustered at the individual level. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

and not statistically significant for the individuals with below median household income in our sample (columns 1 to 3 in Table 4, Panel B). They also spend less money on the purchases of these food categories compared to their higher-income counterparts. In contrast, the treatment effect on rice, snacks, and spices expenditure is larger and statistically significant for the above median income individuals. In the above-median subsample, treatment arm individuals had a substantial and significant relative drop in snacks purchases by 0.158 US$ at PPP (about 34 percent), and a 0.170 US$ at PPP increase in weekly spices purchases. This pattern is consistent with cash-constrained individuals not being able to afford basic food needs and investing the financial liquidity induced by subsidies into food products, instead of substituting away from purchasing products like rice and snacks.

A drawback of scanner data is its limitations in capturing the individuals' full purchasing volume. For instance, 18 percent of the individuals did not purchase any snacks during the pre-intervention period. This might be because some individuals do not buy snacks or they might make their snacks purchases in a grocery that is not covered in our experiment.[24] To examine the treatment effect on those whom we observe making a purchase of the focal product, we split the sample based on pre-intervention purchasing behavior. In Table 4, the no-purchase section (columns 1,2 and 3) of Panel C consists of individuals who never purchased rice, snacks or spices in the pre-intervention period, respectively. Although there is a small level of purchasing in these categories during the intervention period, we see no significant treatment effect on this subsample. In contrast, we observe an increase in the effect sizes on the sample who made a purchase of the focal product during the pre-intervention period, compared to the full sample. For instance, rice purchases dropped by 0.589 US$ at PPP (or 45 percent compared to the control arm mean), as opposed to 0.245 US$ at PPP drop (about 35 percent) in the full sample. We observe a similar pattern for snacks and spices. These results suggest that the point estimates of our main results in Table 3 could be larger for the broader shopping patterns of our target population. They are also consistent with subsidies having larger effects on the intensive margin (e.g., increasing the amount of spices purchases for those who do buy prior to the intervention) compared to the extensive margin (e.g., generating spices purchases for those who do not buy).

2.E Nutritional outcomes

We next consider the differences in nutritional purchases in Table 5. To do so, for each purchased product, we recorded the nutritional value of the purchased item (details available in Online Appendix A.B). An average individual in the control arm purchases food products worth of about 1,498 calories per day in our partner stores. This amount is lower than the average daily caloric consumption of roughly 2000 calories for a low-income urban settlement dweller in India (Deaton and Drèze, 2009; Sharma et al., 2020) but is higher than the 1400 calories per capita per day estimated consumption for the poorest individuals in India (Duflo and Banerjee 2009, page 61).[25]

We find no statistically significant spillovers on nutrient purchases. Individuals in both trial arms had similar levels of caloric, macro nutrient (protein, fat, and carbs) and micro

[24] Because the assignment to the treatment is randomized, such data leakage is expected to be balanced across the trial arms.

[25] It is possible that the person we track may buy food for more than one person. At the baseline 28 percent of the individuals self-reported being the household's main shopper for unhealthy food products. In contrast, 44 percent reported other family members being the household's main unhealthy food buyer. Others reported equal distribution among household members. For cereals, 51 percent of the individuals reported being their household's main buyer, and 27 percent reported otherwise.

nutrient (Iron, Calcium, and Zinc) purchases. There is an insignificant increase in weekly caloric purchases, of 1,687 calories, and a mildly significant increase in Iron purchases by 17 micro grams, which is not robust to multiple hypothesis testing. We also find no evidence of spillovers in unreported subsample analyses.

Table 5: Effect of Food Subsidies on Nutritional Purchases

	Calories (1)	Protein (2)	Fat (3)	Carbohydrates (4)	Sugar (5)	Iron (6)	Calcium (7)	Zinc (8)
ITT	1,687.272	-5.719	41.851	-70.817	-19.137	17.149*	132.469	0.205
	(1,640.517)	(12.856)	(34.009)	(81.582)	(17.932)	(10.268)	(239.433)	(0.521)
LATE	2,055.977	-6.969	50.997	-86.292	-23.319	20.897*	161.416	0.250
	(1,999.005)	(15.666)	(41.441)	(99.409)	(21.851)	(12.511)	(291.755)	(0.635)
Sharpened-q	1	1	1	1	1	1	1	1
Control Mean	10,488.03	169.57	298.06	1,071.43	189.14	61.469	1543.38	1.32
[Std dev]	[34,568]	[510.45]	[772.17]	[3,124.15]	[641.93]	[218.06]	[8512.1]	[8.041]
Observations	22,236	22,236	22,236	22,236	22,236	22,236	22,236	22,236

Notes: This table presents the main estimates for nutritional purchases. Outcomes are at the person-week level and reported here in levels. Calories are measured in kcal, macro nutrients (columns 2 to 5) measured in grams, and micro nutrients (columns 6 to 8) measured in micro grams. ITT row reports the intention-to-treat (equation 1) and LATE row reports the local average treatment effect (equation 2) estimates, respectively. Both regressions include individual and week-in-panel fixed effects. Standard errors are clustered at the individual level. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

These results have several policy implications that may be worth highlighting. The absence of negative spillovers on transaction data suggests that in-kind food subsidies have a net-positive direct impact on nutrition – provided that beneficiaries consume the subsidized products. Although we observe both complementarity and substitution effects across various food products, all-in-all these effects cancel out and the nutritional impact of a food subsidy equates to the nutritional values of the subsidized food. This raises the question, subject to the same budget constraint, whether one can design a nutritionally more effective subsidy program by changing the selection of subsidized products.

3 Alternative explanations and limitations

3.A Presence of government food subsidies

Participants' access to government subsidies during our study period could imply that our main estimates in Tables 3 are extra-marginal to PDS. To test the robustness of our analysis, we separately study individuals from our sample who would ideally receive food subsidies but are unable to do so due to inefficiencies in the targeting of PDS. There are two factors specific to urban settlements that reduce the access to the PDS network. First, because the community we conducted our experiment is an informal settlement, 13 percent of the respondents lack formal documentation – e.g., an electricity bill – to apply for a ration card, despite having low earnings. Second, one can access PDS subsidies only at the state they registered to the program.[26] A further 17 percent of our sample are unable to access government subsidies due to being registered in a different state.[27] We find no statistically significant differential treatment effect across nine outcome variables except for accompaniments, where the treatment effect increases for the sample who do not have access to PDS (see Online Appendix, Table A.10). Also, the endline survey suggests that the take-up frequencies of PDS-eligible individuals are statistically indistinguishable across the two trial arms during the study period – ruling out the possibility that individuals substitute away from their PDS subsidy for our experiment subsidies.

3.B Effects on market prices

A consequence of our randomized trial (a random assignment to our self-operated food subsidy program) was to reduce the demand for rice in grocery stores in our sample. Thus, one can expect that our intervention in the Mankhurd community may shift the supply-demand balance for certain product categories, and possibly affect the market prices.[28] Such market price externalities on the control arm would violate SUTVA by creating interference between the treatment and control arms. We first estimate the line item-level price changes before and after the start of the experiment. Next, as rice and wheat are the products that we subsidized, in a two-way fixed effect model, we study the differential effect of the starting of the experiment on rice and wheat using all other line-item prices as a control arm. Estimates presented in Table A.13 suggest that starting of our experiment had no detectable effect on the market prices.

[26]Note that to address this issue of migrants' access to PDS, India initiated the one nation one ration card program. Details at https://static.pib.gov.in/WriteReadData/userfiles/one_nation.pdf The program had first launched in Mumbai in 2020. However, our pilot interviews and baseline surveys indicate that during our study period, it has not been extensively implemented in the community where we run the experiment.

[27]In total, 574 individuals stated they do not take-up the PDS subsidies. Among this sample, 196 individuals reported a lack of formal documentation. Another 218 were unable to access PDS subsidies due to being registered in a different state, out of which 156 individuals were unaware of the one nation one ration card program, and further 57 stated the program does not work in Mankhurd. 82 individuals stated they do not take up their subsidies due to several reasons including losing their ration card, having problems with store agents, and not liking the quality of products offered in the program. Another 78 did not state any reason. We only focus on the sample who do not have access due to a lack of formal documents or for being registered in a different state.

[28]Note that, depending on the sign of the price-demand slope, the market prices could increase or decrease. For instance, in the case of a Giffen good (as in Jensen and Miller (2008)), deployment of food subsidies might increase market prices for subsidized products.

3.C Stockpiling

Treatment arm respondents might channel their savings towards stockpiling products for the post-treatment period. Such behavior would result only in a temporal shift of food purchases and purchase patterns would not change if the program was implemented for a longer period. Under this explanation, in the post-treatment period, one would expect treatment arm respondents to purchase less of the products they stockpiled during the experiment since they would have excess inventory at home. To test this, we dropped the 6-week subsidy period data and used the 2-week post-subsidy data instead. In essence, we estimate the impact of a random assignment to the treatment arm from pre-subsidy to post-subsidy period on grocery spending. We find no evidence for stockpiling (see Online Appendix Table A.14). The relative grocery expenditure patterns for almost all products in two trial arms during the 2-weeks post-subsidy period go back to the pre-treatment levels. The only exception is spices. In fact, against the stockpiling hypothesis, we observe that post-intervention, individuals in the treatment arm maintain a significantly higher level of spices expenditure relative to the control arm.[29]

3.D Household level outcomes

Our treatment assignment and corresponding main analyses are at the individual level. However, dietary decisions are often made at the household level. To address this issue, in the baseline survey, we collected each participant's household members' names and phone numbers. Next, based on this information, we aggregate our scanner data at the household level.[30] Our household-level estimates on expenditure and nutritional purchases are presented in Online Appendix Tables A.11 and A.12. The results confirm our main estimates in Tables 3 and 5, respectively, except that snacks and soft drink purchases are in the same direction but lack statistical significance.

3.E Forward-looking behavior

To establish fairness, as well as compliance, we offer control arm respondents food subsidies 2 weeks after the end of their 6-weeks experiment period. Forward-looking respondents in

[29]Note that the high post-treatment expenditure in spices is unlikely due to potential stockpiling of subsidized products during the treatment period since that would imply a significant relative drop in the subsidized goods expenditure in the same period.

[30]Note that there were 26 households where more than one household member was enrolled in the experiment. We define a household being treated if at least one household member is assigned to the subsidy treatment, and control if no household members receive our food subsidies.

the control arm might optimize their food shopping behavior during the experimental period according to the predicted effects of the food subsidies they will receive in the future. Such behavior would be rational and consistent with the life-cycle hypothesis (Ando and Modigliani, 1963). Note that, the anticipation of a food subsidy would cause the control arm respondents to exhibit shopping patterns similar to the treatment arm respondents, leading to underestimation of our treatment effects. Nevertheless, we restrict our attention to the control arm sample, and use the staggered enrollment in our study to identify the potential impact of being recruited to the control arm. Individuals who are enrolled in the study at a later date serve as a control benchmark for the forward-looking (or placebo) effects of being administered to the control arm of the study. Estimates presented in the Online Appendix Table A.15 provide no evidence for this hypothesis.

3.F Sample representativeness

The majority of individuals that we invited has joined our study (see Online Appendix Table A.7). However, individuals who were willing to join the experiment may not reflect the shopping patterns of the broader urban settlement population. Moreover, we invite individuals who regularly shop in our partner stores (seen at least twice prior to start of the experiment – more than five weeks ago and in the last two weeks). These regular shoppers may have different food shopping patterns compared to other customers of our partner stores, leading to a potential sample selection.

These predictions are not borne out by the data. We record all the transactions in our partner stores. This includes customers who did not want to join the experiment or those who were not satisfying our inclusion criteria. We use this data to compare the basket-level shopping characteristics of our experiment sample with all other tagged customers who were not in our experiment. Online Appendix Table A.21 presents the results. Before joining the experiment, average shopping basket of a customer in our experimental sample is statistically indistinguishable from the shopping basket of a customer who is not in our experiment in terms of money spent and quantity, calories, or macronutrients purchased.[31]

[31] We focus on the data collected prior to July 1, 2022, the date in which the sample to invite to the experiment was determined.

3.G Alternative model specifications and outcome variables

Our main results in Table 3 are robust to various alternative specifications. We first restricted our attention to 6-week experiment period, and estimated the following linear regression model: $Y_{it} = \alpha TREAT_i + \psi X_i + \zeta_{it}$. In Online Appendix Table A.16, Panel A, we estimate this model without any controls, in Panel B, we add time fixed effects for each start date of the week. Finally, in Panel C, we add controls – variables reported in Online Appendix Table A.1 – using double lasso (Belloni, Chernozhukov and Hansen, 2014). Next, in Online Appendix Table A.17 we turn to our main model in equation (1). In Panel A, we apply a natural logarithmic transformation to our outcomes after adding 1. In Panel, B we consider an alternative clustering structure of errors with two-way (individual and week-in-panel) cluster-robust standard errors instead of clustering at the individual level. In Panel C, we change the outcome variable to the count of the number of shopping trips that include the focal product category (e.g., number of rice trips), and in Panel D, we report the estimates on the variety of the focal category purchased – measured as the unique number of SKUs (e.g., basmati and jasmine rice). Across all these models, the results confirm the main estimates, except for a few cases where the effects have the same direction but lack statistical significance. Those exceptions are spices and soft drinks as well as the variety and the number of shopping trips for rice, snacks, and ready-to-eat products.

Finally, we include calendar week fixed effects in our main model, by using the start date of each week-in-panel to define the calendar week. Estimates on grocery expenditure, nutritional purchases, and heterogeneous treatment effects are qualitatively similar to our main results. See Online Appendix Tables A.18, A.19, and A.20.

4 Conclusion

In this paper, we analyze the effects of an in-kind food subsidy program on low-income individuals' food purchasing patterns and corresponding nutrient purchases. In an urban settlement in Mumbai, India, we opened a subsidy store that mimics the government's food subsidy program, and randomly assigned individuals to a food subsidy program in a field experiment. We recorded individuals' food transactions across 39 food-selling vendors such as groceries, butchers and dairies, by equipping these stores with scanner devices. This real purchase data enables objective tracking of individuals' nutrient purchases.

We find that low-income consumers purchase more calories from packaged snacks than from rice and wheat combined, an effect that is more prominent among working parents. Taken together with earlier findings on hidden hunger in India, which indicate that malnourished individuals get enough calories but lack important micronutrients (Harding, Aguayo and Webb, 2018), our results provides suggestive evidence that heavy consumption of snacks could constitute a reason for this phenomenon.

We find that random assignment to our in-kind food subsidies causes a significant increase in the purchases of supplementary food, such as spices or accompaniments. This increase supports the hypothesis that individuals increased consumption of home-cooked meals. In tandem, we see a significant drop in packaged snacks, soft drinks, ready-to-eat food and nuts purchases. Speculatively, these results might be explained by individuals filling their stomachs with home-cooked meals, which concomitantly leaves less appetite for snacking out.

From a nutritional standpoint, we find no negative or positive spillovers on the food purchasing scanner data. Individuals in both trial arms purchase quantities of calories, carbohydrates, protein, fat, and several micronutrients that are statistically indistinguishable. Therefore, provided that treatment arm individuals consumed their food subsidies, our results suggest that in-kind food subsidies have a net impact on individuals nutrition, but it is limited to the nutrients provided in the program.

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A Materials and Methods

A.A Experiment Protocol

Partner Stores. We install point of sale scanner devices in 39 local stores in the Mankhurd settlement. We selected all our partner stores in the same locality to saturate an area and capture as many bills as possible from individuals shopping from that neighbourhood. Most of our partner stores have a similar structure, but the exact assortment offered varies depending on the store size. We also partner with two butchers, two fruit and vegetable vendors, and a street food seller.

We offer a weekly monetary incentive of Rs. 1,000 to each store, and we provide the scanner device free of charge. We capture every transaction occur in a partner store via producing a bill for each shopping basket. This includes scanning each product, manually entering the sales amount for the non-barcoded items, and tagging a bill with a unique customer identifier.[32] The data we collect via the POS device includes the product codes and names of all items in a shopping basket, their sales price, customer identifier, and a transaction timestamp. Once we install a device to a partner store, we have a one week lead-in period. During this period, we train the store owners to use our scanner devices. Data collected during this week is not used in the analysis. To ensure data quality, we deploy extensive local research assistant involvement in the stores, and conduct periodic data verification tests.

Store Research Assistance and Mystery Shoppers. We take two steps to verify that partner stores use the devices as intended in the experiment design. First, we place full time research assistants in our partner stores. This is to ensure that all shopping bills are accurately recorded. Second, we employ mystery shoppers (undercover enumerators). These individuals are not in either the treatment or the control arm; instead, they will be a part of the quality control system for the collection of scanner data. We craft arbitrary shopping baskets for these mystery shoppers, and via the scanner data gathered for them, we check whether the stores (or store RAs) tag these customers and accurately capture their shopping baskets. The store owners are provided a financial incentive for producing the mystery shoppers' bills (i.e., the full basket and customer tag for each store visit). Note that these payment-based mystery-shopper quality

[32] By requesting customers who shop at these stores to share their details (name and details), we 'tag' customers, and obtain shopping basket data with customer tags through the scanner data collected in our partner groceries.

checks ensure the incentive compatibility of our data collection procedure.

Incentive Program. At the end of the study, we conduct a lottery event, at which we provide various incentives to the participants in our experiment. To increase participation in the study, we inform participants about this event in advance. The lottery event is intended to mimic an incentive program. It ensures that participation in our study (which entails providing one's customer details during the billing process, on shopping trips to our partner stores) is incentive compatible.[33]

Pre-experiment Data Collection, Recruitment and the Baseline. Once the store setup is completed, the pre-intervention data collection period begins. The data collected during this period is also used to identify the set of customers that we invite to our experiment. To do so, we sampled from the set of customers whose first shopping instance was at least 5 weeks ago, and the last shopping instance was at most 2 weeks ago. We impose this inclusion criteria to eliminate occasional shoppers (e.g., customers who do not live in Mankhurd but made a shopping in a partner store while passing by). Surveyors reach out to participants via phone calls and invite them to our experiment. If a respondent agrees to join to our study, surveyor schedules an in-person meeting to administer the baseline survey, and enroll respondent into to study. The baseline survey includes the consent form, a demographics questionnaire, and a battery of questions around their food preferences and habits. More details about the survey variables can be found in Section A.B. Those successfully complete the baseline survey is randomized into an experiment arm. During the baseline participants are informed about the delivery method of the subsidy program, and provided with a printed subsidy coupon (see Figure A.8).

Food Subsidy Delivery. We rent an office with a street facing counter in Mankhurd. Our subsidy store is located in a central location in Mankhurd, and it is in close proximity to our partner stores. All food items are stored and distributed via this office. The subsidy store operates 7 days a week, between 08.00-15.00 and 16.00-22.30. Subsidies are offered on a weekly basis throughout the treatment period. Respondents in the treatment arm can take-up of their weekly subsidies by coming to our subsidy store. A subsidy that is not taken-up of in any week will not be accessible in the following week. To run the subsidy store, we placed two

[33]Note that we do not specify how exactly the lottery system works (i.e., we did not reveal whether they will get a lottery ticket per bill or per day) to avoid strategic changes in the shopping behavior. Importantly, the area we run our experiment is a localized community, where kirana stores (or our RAs, after their training) personally know majority of their regular customers. Also, the scanner device saves customer details. Therefore, once a customer's first bill is tagged, in all subsequent transaction, we were able to automatically select from their previously saved customer's list. This significantly reduces the search cost.

RAs, one is responsible for the delivery of the food, whereas the other records the transaction. Subsidy transactions are recorded electronically via a relational database that we build for this purpose (see Figure A.5). Note that to avoid any potential experimenter demand effects that could lead respondents to shop differently in partner stores due to assignment to a trial arm, we executed the scanner data collection as disjoint operation from the rest of the study. Namely, we recruit and manage two separate teams of RAs to independently operate the scanner data collection process and the subsidy and survey data collection process. All treatment arm respondents are informed that reselling the food subsidies would result in immediate dismissal from the experiment. We conduct semi-structured audits in the community to track such reselling behavior.

A.B Variable Construction

Nutrition Mapping and Product Quantities. We build a database that contains information of all products sold in our partner stores, including item's net weight, nutritional components, and categorization. In total, our data consists of 10119 unique product-store pairs.[34] The 8,298 of food products are packaged goods and 1,821 are loose items.

For packaged items, we design a software interface for field research assistants that will help them digitally record the information on product's net weight and nutritional components. An RA logs into the smartphone app with a store identification number and the app will return a list of names of packaged products in that store. The RAs task is to record the net weight of a product and record the nutrient information printed on each product's package. Note that consumer packaged good companies are mandates to report the nutritional information of food items.[35]. For validation, we selected 25 most frequently purchased items from each store, and 10 additional randomly selected product. Then we asked the RA to take a photo of the nutritional table of these items. We then compared the nutritional information shown in the photo with the ones in our database.

For food products that are sold in loose, we use the Indian Food Composition Tables 2017 (IFCT) published by the National Institute of Nutrition as part of the Ministry of Health and

[34]Note that products that does not have a bar code (e.g., loose items) are initially named manually by the research assistants within each store independently. Consequently, the name of a product may not be universal across our partner stores. We relabeled products to ensure the names are accurate in our final transaction data. However, to avoid the potential human errors, we collect the nutrition information of all food items at each grocery separately.

[35]See https://www.fssai.gov.in/upload/uploadfiles/files/Packaging$_{L}abelling_{R}egulations.pdf$

Family Welfare, Government of India.[36] During each transaction, store RAs record the quantity of the sales amount in grams (or milliliters for drinks). Note that before each sales instance, store owners weight the loose products to calculate the price that customer needs to pay. Therefore, we have access to timely and reliable information on the each product's quantity. Also, the final price written on the bill is a deterministic function of the quantity that store RAs enter manually.

There is a third set of food products, which we refer to as self-packaged. Self-packaged goods are the products that are produced locally (e.g., by the store owners). Majority of these products are street food (e.g., samosa), but there are also products sold in groceries such as a pouch of drinking water packaged by store owners. As these are informally produced goods, they lack nutritional details on the product's package or in the IFCT database. There are a total of 826 self-packaged items, and they cover less than 3 percent of the total transaction volume of our data. For these products, we used two data sources. First, the the USDA National Nutrient Database (NND) for Standard Reference, Release 28 (2015).[37] Second, MyFitnessPal library.[38] Note that these sources are not tailored for a low-income community where package sizes tend to be smaller. For the most common 10 self-packaged goods, which cover over 85 percent of all self-packaged goods transactions, we purchased 5 units of each product and weight them. Then, we recalibrate the quantity values of our products.

Product Categorization. Three research assistants – two of which are based in South India, and one of which is based in North India –independently categorized all products in our data.[39] Next, we combined the categorization schemes developed by each RA. If all three RAs independently agree on the category, which was the case for 94 percent of the products in the first round, we assigned the product into that category. For the remaining products we send the list of product names back to RAs for re-categorization and repeated the same process for two more rounds. Finally, a fourth RA has conducted an independent audit study on the product categorization (along with the accuracy of products' nutritional details).

Survey-based Measures. Besides the scanner data, we also collect survey data at the baseline and the endline. Baseline survey is conducted before during the administration of an individual to the experiment, before the randomization. The endline survey took place between the fourth

[36] Available at http://www.ifct2017.com/frame.php?page=home
[37] Available at https://www.ars.usda.gov/Services/docs.htm?docid=8964
[38] Available at https://www.myfitnesspal.com/nutrition-facts-calories
[39] Note that except for tobacco products all non-food items fall under the same "non-food" category.

and the sixth week of the treatment period. Surveys are conducted in-person.

- *Food Insecurity.* We adopted a shortened version of the Household Food Insecurity Access Scale (baseline and endline).[40]
- *Socio-economic background:* Demographics, employment and earnings, household composition (baseline).
- *Food purchase behavior and shopper characteristics:* A list of questions reflecting individuals food shopping behavior. Including the stores they shop at as well as questions on expenditure, frequency and preference (baseline and endline).
- *Overall Expenditure:* A list of questions on non-food commodities including travel fare, beauty, technology, repair and maintenance, religious services, recreational and cultural, alcohol, lottery, energy, education, medical, hygiene and toiletries (baseline and endline).
- Self-reported happiness and life-satisfaction (baseline and endline).

B Additional exhibits for the experiment

Figure A.1: Study Location Geopmap

Notes: This figure depicts the study location. Blue pins reflect the stores in our study. Red pins reflect remaining food-selling vendors. Yellow pin is our subsidy office.

[40]Available at https://www.fantaproject.org/sites/default/files/resources/HFIAS$_{E}NG_{v}3_{A}ug07.pdf$.

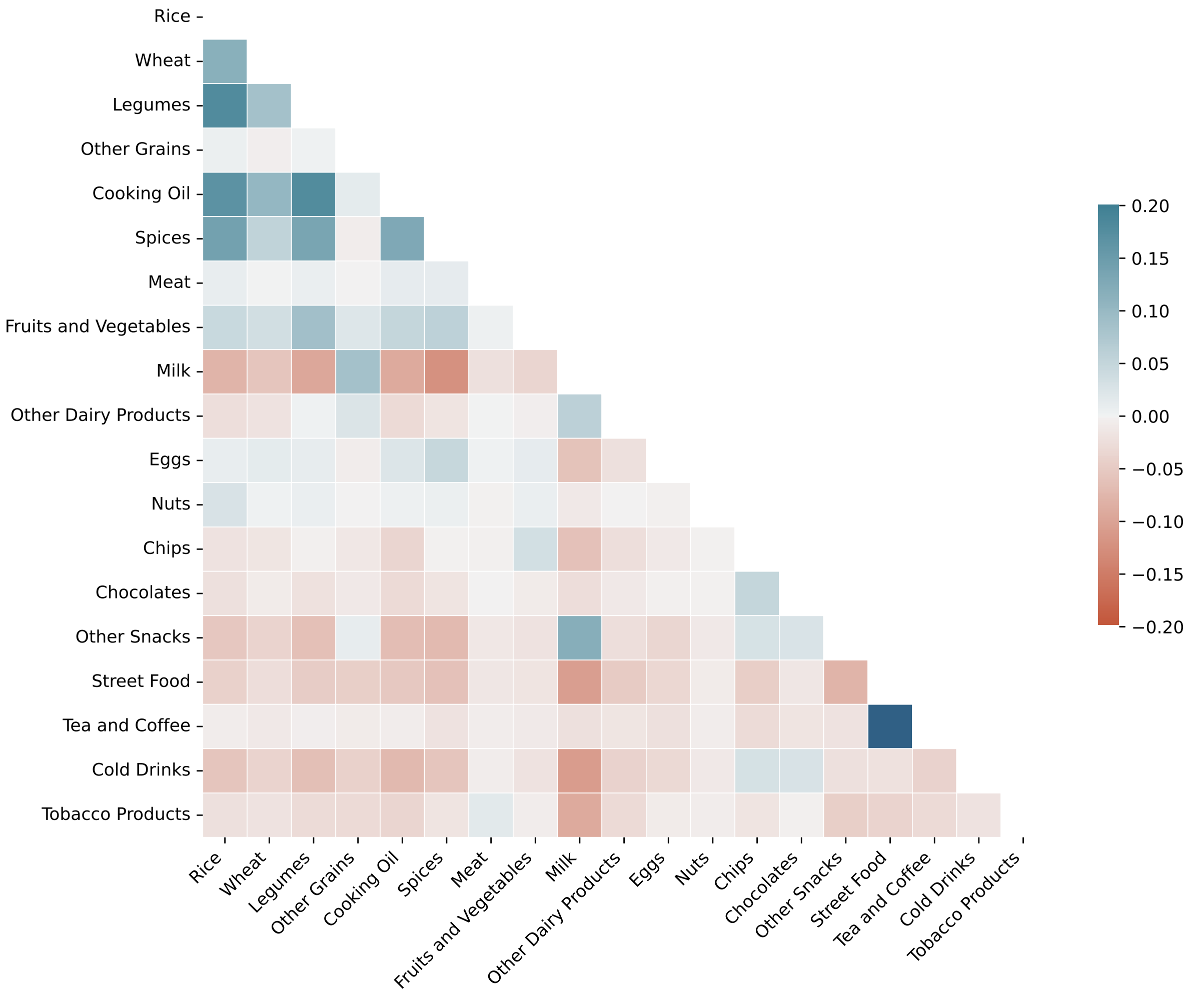


Figure A.2: Correlation Among Product Co-purchases

Notes: This figure depicts the correlations between a customer's co-purchasing of two products in the same hour. Blue and reddish colors reflect a positive and negative correlation, respectively. Estimates over 0.2 are colored as dark blue (i.e., tea and coffee with street food).

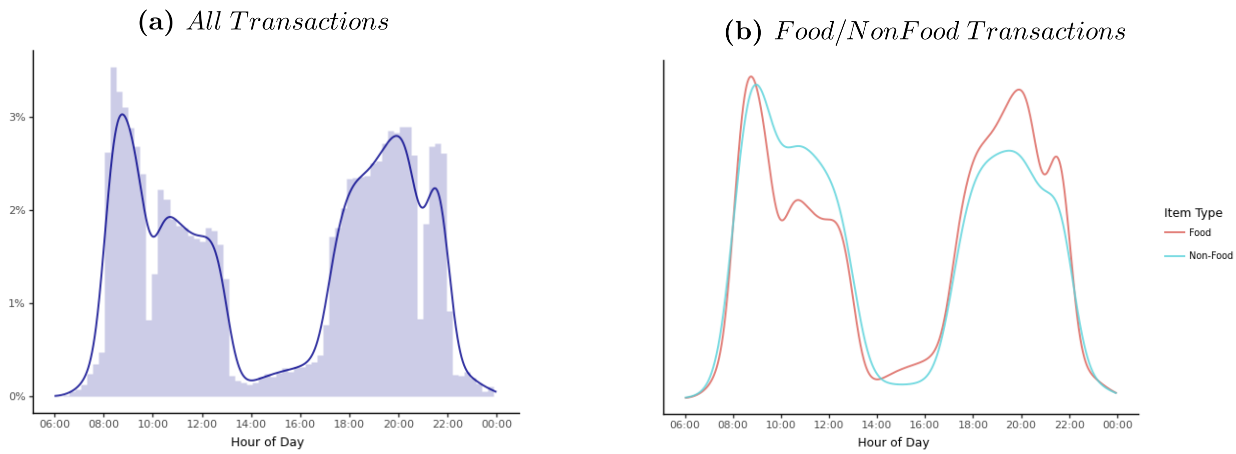
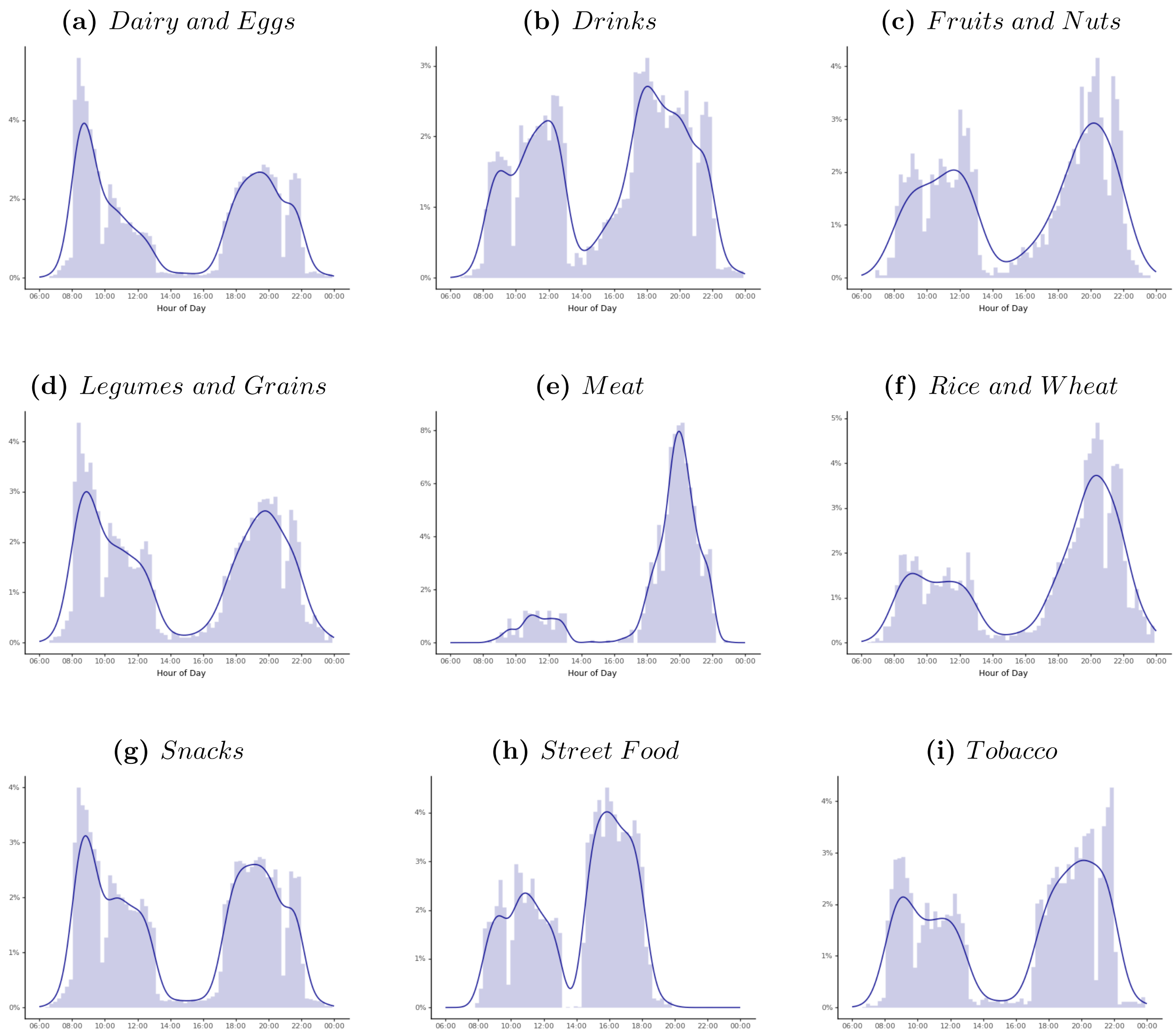
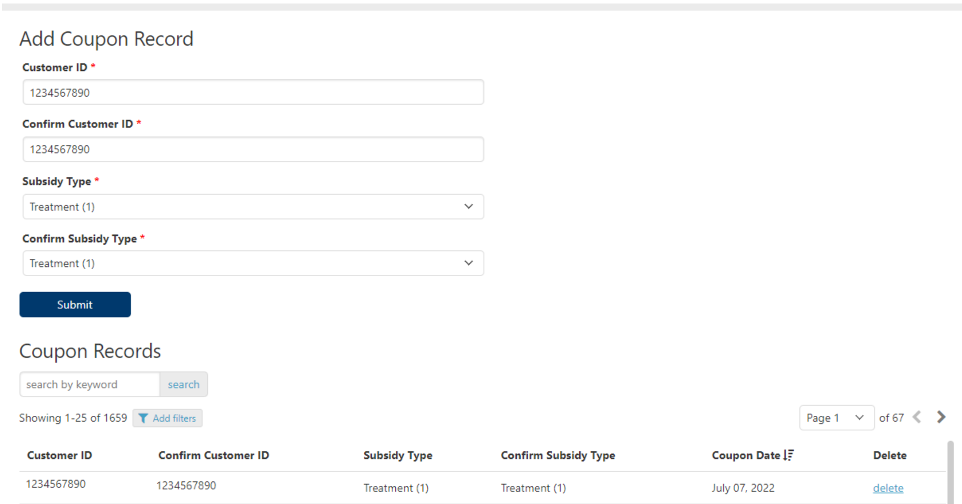


Figure A.3: Density plot of purchases by category and the time of day

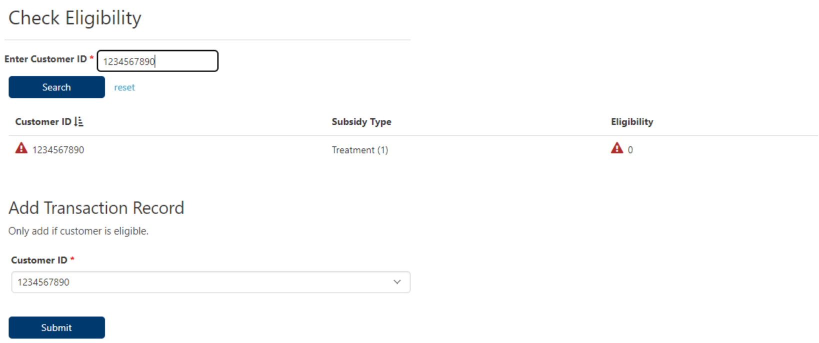


(a) *Dairy and Eggs* **(b)** *Drinks* **(c)** *Fruits and Nuts* **(d)** *Legumes and Grains* **(e)** *Meat* **(f)** *Rice and Wheat* **(g)** *Snacks* **(h)** *Street Food* **(i)** *Tobacco*

Figure A.4: Density plot of purchases by category and the time of day

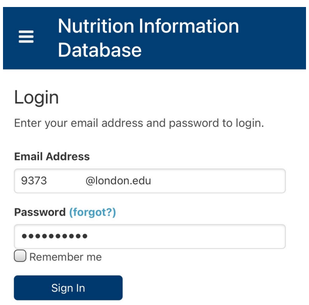


(a) Page to register respondents to the subsidy program

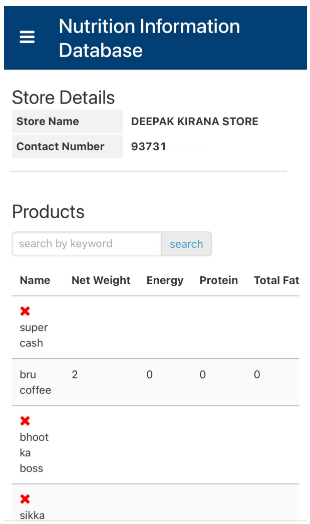


(b) Page to record the subsidy transactions

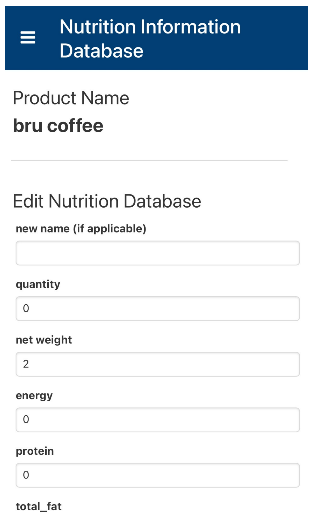
Figure A.5: User Interface of the Software Developed for Subsidy Transaction Relational Database



(a) *Login*



(b) *Store*



(c) *Item*

Figure A.6: User Interface of the Software Developed for the Nutritional Database Collection

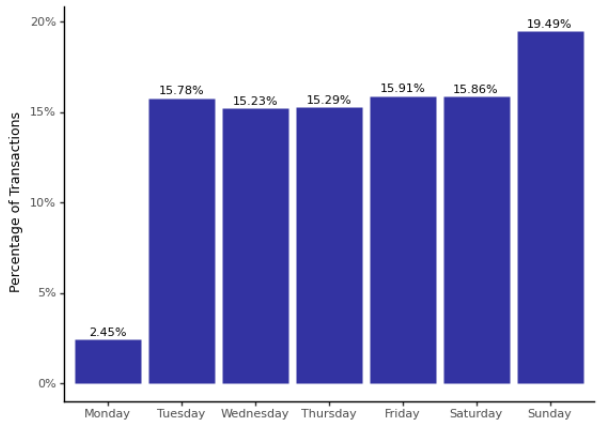


Figure A.7: Distribution of Store Traffic by Day of Week

(a) Subsidy Treatment Coupon

(b) Control Arm Coupon

Figure A.8: Printed Coupons for the Treatment (above) and the Control (Below) Arms

Table A.1: Balance Across the Trial Arms

	Treatment Arm (1)	Control Arm Plan Arm (2)	Balance test p-value (1) - (2)
Age	32.334	32.889	0.336
	(9.866)	(10.115)	
Gender	0.330	0.360	0.272
	(0.471)	(0.480)	
Any High School Education	0.304	0.354	0.068*
	(0.460)	(0.478)	
Employed	0.644	0.628	0.564
	(0.479)	(0.484)	
Income US$ PPP	834.308	817.739	0.541
	(472.160)	(461.495)	
Daily Wage Worker	0.136	0.157	0.306
	(0.343)	(0.364)	
Religion (Hindu)	0.724	0.744	0.430
	(0.447)	(0.437)	
Interstate Migrant	0.684	0.652	0.236
	(0.465)	(0.477)	
Self-Employed	0.126	0.124	0.917
	(0.332)	(0.330)	
Married	0.726	0.772	0.065*
	(0.446)	(0.420)	
No Formal ID or bills	0.274	0.255	0.445
	(0.446)	(0.436)	
Number of Household Members	4.920	4.885	0.758
	(2.071)	(1.880)	
Any Children Under Nine	0.464	0.475	0.704
	(0.499)	(0.500)	
Income per HH member (Rs.)	4,269.182	4,248.783	0.916
	(3,236.758)	(3,378.490)	
Share of HH Income Spent on Food	0.629	0.622	0.795
	(0.438)	(0.503)	
Weekly HH Rice Purchase (Kg)	7.705	7.722	0.932
	(3.506)	(3.517)	
Weekly HH Wheat Purchase (Kg)	7.740	7.775	0.863
	(3.463)	(3.485)	
Vegetarian	0.848	0.844	0.860
	(0.359)	(0.363)	
Has Tuberculosis in the Family	0.088	0.069	0.205
	(0.284)	(0.253)	
Observations	500	758	1,258

Notes: This table presents balance checks for the variables related to the baseline survey administration across the subsidy treatment and control arms. Columns 1 and 2 contain the means and standard deviations for individuals in each arm. Column 3 contains p-values for the test for equality of means between the treatment and control arms. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.2: Mystery Shopper Validation Checks

Event no	First-time shopper	Regular Shopper
1	0.84	1.00
2	0.96	1.00
3	0.92	1.00
4	1.00	1.00
5	1.00	1.00
6	0.92	1.00
7	1.00	1.00
8	1.00	0.96
9	0.96	1.00
10	0.96	1.00
11	1.00	1.00
12	1.00	1.00
13	0.88	1.00
14	1.00	1.00
15	1.00	1.00

Notes: Columns reflect the success rate from each mystery shopper validation test round. During May-October 2022, we conducted fifteen mystery shopper events, where each event has taken place over the course of a week. At each event, we made two unannounced visits to a randomly selected 25 partner stores. One with a regular customer, and another with a new customer that has not shopped at the partner store before. We made this distinction because once a customer's details are collected, recording the subsequent transactions are considerably easier. Both mystery shoppers were undercover enumerators that were not known to our field research assistants or the store owners.

Table A.3: Correlation Between Parental Status and Expenditure on Food and Tobacco Products

	Rice (1)	Rice (2)	Snacks (3)	Snacks (4)	Spices (5)	Spices (6)	Tobacco (7)	Tobacco (8)
One Child or More	0.038	-0.045	0.173***	0.165***	0.040	0.028	-0.060*	-0.050
	(0.096)	(0.110)	(0.035)	(0.038)	(0.037)	(0.042)	(0.035)	(0.035)
Female		0.035		0.053		0.044		-0.046
		(0.161)		(0.052)		(0.056)		(0.037)
Number of Household Members		0.014		0.023***		0.019**		0.006
		(0.021)		(0.009)		(0.008)		(0.006)
Age		0.005		-0.004**		-0.001		-0.001
		(0.006)		(0.002)		(0.002)		(0.002)
Employed		0.069		-0.035		0.032		-0.008
		(0.154)		(0.051)		(0.050)		(0.046)
Avails of Government Subsidies		-0.046		-0.013		-0.014		-0.016
		(0.096)		(0.037)		(0.033)		(0.034)
Interstate Migrant		0.183*		0.042		-0.074**		0.034
		(0.097)		(0.036)		(0.038)		(0.029)
Had Tuberculosis in the family last year		0.079		0.017		0.015		-0.058**
		(0.198)		(0.059)		(0.060)		(0.023)
Soft Drinks Expenditure		0.047		0.380***		0.071***		0.053***
		(0.034)		(0.051)		(0.021)		(0.017)
Constant	0.593***	0.248	0.266***	0.193**	0.301***	0.241***	0.142***	0.140*
	(0.077)	(0.257)	(0.024)	(0.080)	(0.031)	(0.086)	(0.034)	(0.079)
Observations	22,236	22,236	22,236	22,236	22,236	22,236	22,236	22,236

Notes: Outcomes are at the person-week level and reported here in levels (US$ PPP). Outcome variables and soft drinks expenditure are measured via scanner devices. All other variables are survey-based measures. Standard errors are clustered at the individual level. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4: Data Collection Summary

Data collection window	March 10 to October 5, 2022
Total number of transactions	777,980
Total number of shopping bills	542,679
Unique number of tagged customers (i.e., a unique customer identifier)	23,719
Unique number of tagged customers with a verified phone number	19,154
Number of verified customers with at least 3 shopping bills	12,555
Number of verified customers with at least 5 shopping bills	10,212
Number of verified customers with at least 10 shopping bills	7,387
Number of verified customers that shops in at least 2 different stores	8,152
Number of verified customers that shops in at least 3 different stores	5,301
Number of verified customers that shops in at least 5 different stores	2,299
Share of tagged bills	84.05%
Average number of bills per tagged customer	23.81
Median number of bills per tagged customer	5
Average number of unique stores visited per tagged customer	2.21
Median number of unique stores visited per tagged customer	1
Average number of bills per tagged frequent customer	35.63
Median number of bills per tagged frequent customer	13
Average number of unique stores visited per tagged frequent customer	2.82
Median number of unique stores visited per tagged frequent customer	2
Mean customer inter-shopping time in our partner stores	2 days, 23 hours, 47 mins
Standard deviation customer inter-shopping time in our partner stores	8 days, 4 hours, 2 mins
Median customer inter-shopping time in our partner stores	21 hours, 31 mins

Notes: Until mid June, we gradually expanded our store coverage. A bill is tagged if the transaction records include a unique customer identifier (i.e., a phone number and an optional name). Inter-arrival times were calculated using data from customers with 3 or more shopping bills (i.e., frequent customers).

Table A.5: Basket-level characteristics, Conditional on Observing a Category

Conditional on	Money spent on the focal product (1)	Total money spent on food (2)	Total money spent (3)	Total quantity (4)	Total calories (5)	Total carbohydrates (6)	Total protein (7)	Total fat (8)	N (9)
Accompaniments	13.041	70.235	82.710	111.557	3642.934	441.006	59.637	107.953	1390
	(21.672)	(318.066)	(382.709)	(132.023)	(18409.123)	(2122.304)	(319.477)	(622.193)	
Cooking oils	103.809	161.798	170.181	619.950	8746.685	751.837	110.359	601.764	22228
	(168.804)	(272.811)	(300.154)	(916.262)	(14275.833)	(2249.127)	(292.61)	(805.561)	
Dairy	25.813	33.933	35.220	515.528	2223.142	131.893	30.997	65.294	116141
	(25.355)	(60.503)	(66.462)	(444.185)	(14477.859)	(583.508)	(75.961)	(270.502)	
Eggs	23.465	36.697	38.865	65.506	2481.085	142.242	44.505	68.612	15772
	(22.331)	(63.209)	(70.628)	(116.985)	(15560.595)	(953.49)	(158.564)	(280.449)	
Legumes	66.335	141.347	155.283	714.611	6762.227	1161.017	239.148	169.406	23039
	(83.459)	(260.185)	(295.967)	(1475.125)	(14654.716)	(2706.962)	(433.146)	(519.376)	
Nuts	78.066	178.930	200.433	240.631	5507.809	755.605	152.859	241.800	2310
	(185.71)	(428.109)	(492.144)	(318.608)	(15474.027)	(2256.152)	(365.027)	(763.342)	
Other grains	17.283	42.423	46.421	530.992	9893.710	440.598	61.437	180.382	53495
	(36.336)	(133.725)	(157.607)	(1430.909)	(35841.692)	(1483.892)	(201.743)	(638.352)	
Ready to eat	18.177	95.617	111.314	71.528	4004.602	621.197	97.397	131.650	1416
	(24.723)	(359.445)	(433.765)	(106.413)	(16244.435)	(2880.788)	(392.368)	(628.662)	
Rice	91.470	165.147	177.808	2465.565	12451.467	2482.561	288.193	172.111	15273
	(173.54)	(304.024)	(340.945)	(13833.071)	(51023.384)	(11432.28)	(1150.473)	(492.054)	
Snacks	12.318	29.231	32.651	302.504	2128.859	313.774	30.095	55.113	117111
	(21.051)	(108.704)	(127.902)	(752.79)	(9019.006)	(1124.21)	(141.702)	(245.827)	
Soft drinks	14.445	19.681	20.524	478.661	873.938	90.151	6.484	14.779	30614
	(24.198)	(46.872)	(53.691)	(686.488)	(8352.979)	(339.08)	(47.199)	(163.142)	
Spices	16.309	59.406	67.236	138.692	3030.723	452.762	75.189	97.275	47297
	(27.465)	(179.415)	(209.022)	(250.008)	(12006.665)	(1806.645)	(257.01)	(361.514)	
Tobacco	12.590	15.474	17.407	4.246	249.561	26.402	3.360	6.715	19150
	(10.533)	(23.373)	(25.757)	(25.581)	(3431.696)	(246.015)	(30.263)	(80.734)	
Wheat	97.929	178.791	190.813	3000.219	15340.933	3228.003	440.409	201.007	7194
	(89.242)	(277.557)	(314.408)	(2924.457)	(69918.567)	(15815.636)	(1581.201)	(469.494)	
Other foods	19.774	89.730	102.823	459.091	5177.560	682.064	107.855	126.272	16756
	(31.218)	(242.485)	(288.809)	(889.839)	(20623.42)	(2500.014)	(343.533)	(503.409)	

Notes: This table presents the characteristics of shopping baskets that includes the specified product in the most left column. Column 1 to 3 reports the average money spent on the focal product, overall food and total expenditure, respectively. Column 4 reports quantity in milliliters or grams. Column 5 reports calories in kcal, and 6 to 8 reports carbohydrates, protein, and fat purchases in grams. Column 9 reports the total number of shopping baskets that includes the focal product.

Table A.6: Customers' share of grocery food expenditure across product categories – subsample who purchased at least 3 different categories

	Spending (%)	Count (%)	Calories (%)	Carbohydrates (%)	Protein (%)	Fat (%)
Accompaniments	0.209	0.326	0.128	0.209	0.029	0.058
	(2.18)	(2.017)	(1.794)	(2.695)	(0.494)	(1.265)
Cooking oils	11.848	5.302	12.429	0.434	0.354	28.156
	(18.56)	(8.973)	(20.404)	(4.077)	(3.41)	(37.204)
Dairy	24.006	21.27	15.739	11.3	24.395	24.284
	(26.372)	(21.911)	(24.067)	(20.211)	(29.713)	(31.357)
Eggs	4.022	3.633	1.649	0.057	4.327	3.138
	(9.443)	(7.529)	(6.217)	(1.261)	(12.149)	(10.248)
Legumes	8.736	5.965	6.456	9.393	15.731	1.733
	(14.162)	(9.325)	(12.909)	(17.636)	(23.766)	(7.148)
Nuts	0.786	0.606	0.416	0.322	0.571	0.843
	(4.874)	(2.919)	(3.341)	(2.987)	(4.133)	(5.893)
Other grains	8.216	10.048	16.74	17.03	14.395	12.087
	(11.3)	(11.088)	(27.39)	(25.12)	(22.076)	(23.661)
Ready to eat	0.245	0.359	0.112	0.126	0.23	0.025
	(1.939)	(2.028)	(1.661)	(1.82)	(2.668)	(0.594)
Rice	7.357	3.856	10.575	14.655	10.876	1.721
	(14.609)	(7.457)	(20.127)	(25.563)	(20.705)	(7.004)
Snacks	13.133	21.699	20.437	27.195	11.566	18.167
	(14.35)	(16.974)	(23.91)	(28.208)	(19.226)	(25.137)
Soft drinks	5.2	6.012	2.32	3.234	0.285	0.23
	(11.628)	(10.924)	(8.468)	(10.681)	(3.541)	(3.134)
Spices	6.504	11.716	5.082	5.953	6.978	6.658
	(9.984)	(13.383)	(11.5)	(13.872)	(14.886)	(15.191)
Tobacco	2.621	3.568				
	(9.448)	(10.775)				
Wheat	4.362	1.99	6.375	8.683	7.972	2.419
	(11.696)	(5.621)	(16.454)	(20.777)	(19.205)	(9.371)
Other foods	2.756	3.649	1.543	1.409	2.289	0.481
	(6.846)	(6.199)	(6.91)	(6.128)	(8.508)	(4.077)

Notes: This table presents descriptive statistics on customers' share of food (and tobacco) expenditure in groceries. Here we focus on the sample to customers who purchased at least 3 different categories in our partner groceries. Outcomes are the percentage level.

Table A.7: Recruitment to the Experiment and Response at the Endline

STAGE	Number of Individuals
I. List of Eligible Customers	N = 2,901
Randomly selected subsample	1,800
II. Administration to the Study	N = 1,800
Joined the study	1,258
Invalid phone number	109
Unable to reach the respondent over the phone	214
Not in Mumbai during the study period	107
Not interested in the next stage	112
III. Enrolled in the Experiment	N = 1,258
Treatment arm	500 (39.7 %)
Control Arm	758 (60.3 %)
IV. Endline Survey Responses	N =1,030
Treatment arm	419 (40.6 %)
Control Arm	611 (59.4 %)

Notes: This table shows the enrollment process and response rate for the endline survey.

- Stage I. We identified 2,901 regular customers in our partner stores. We define a customer id as a regular shopper if the individual was seen at least once between June 15 - July 1, and at least once prior to May 15. We randomly selected 1,800 customer ids to invite to the experiment.
- Stage II. We attempted to reach out to 1,800 selected customers, of which 109 were not valid phone numbers. We called each number up to 3 times for the enrollment period and also sent a WhatsApp message (SMS, if the customer did not have WhatsApp). We were unable to contact 214 individuals. 107 individuals were not located in Mumbai, therefore, unable to join our study. There were 112 individuals who stated they were not interested in joining the experiment.
- Stage III. We recruited 1,258 individuals. A participant is assigned to a subsidy treatment arm with 40 percent probability, and to the control arm with 60 percent probability.
- Stage IV. We attempted to conduct the endline surveys four to six weeks after the respondent's enrollment date.

Table A.8: Effect of Food Subsidies on Other Food and Tobacco Expenditure

	Dairy stores (dairy and eggs) (1)	Butchers (meat, fish, and poultry) (2)	Fruits and Vegetables (3)	Street Food (4)	Corner shops (Tobacco Products) (5)	Tea and Coffee (6)
ITT	-0.175	-0.077*	-0.019	-0.005	-0.013	0.012
	(0.118)	(0.045)	(0.014)	(0.017)	(0.017)	(0.012)
LATE	-0.214	-0.094*	-0.024	-0.005	-0.016	0.015
	(0.144)	(0.055)	(0.017)	(0.021)	(0.020)	(0.014)
Sharpened-q	0.468	0.468	0.468	0.655	0.468	0.468
Control Mean	1.489	0.061	0.055	0.088	0.11	0.075
[Std dev]	[3.205]	[0.856]	[0.925]	[0.516]	[0.723]	[0.505]
Observations	22,236	22,236	22,236	22,236	22,236	22,236

Notes: This table presents the main estimates for weekly food expenditure on other food-selling vendors such as dairy stores, butchers, fruit and vegetable sellers, street food sellers (e.g., samosa), and corner shops (tobacco). Outcomes are at the person-week level and reported here in levels (US$ PPP). ITT row reports the intention-to-treat (equation 1) and LATE row reports the local average treatment effect (equation 2) estimates, respectively. Both regressions include individual and week-in-panel fixed effects. Standard errors are clustered at the individual level. Last row reports the sharpened-q values for multiple hypotheses correction. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.9: Effect of Food Subsidies on Shopping Patterns

	Number of unique stores visited	Number of shopping trips	Average shopping basket size	Dietary diversity	Total food quantity (grams)	Total drinks quantity (milliliters)
	(1)	(2)	(3)	(4)	(5)	(6)
ITT	0.004	-0.125	-0.026	-0.267	-66.361	-56.897
	(0.045)	(0.159)	(0.035)	(0.233)	(117.874)	(57.373)
LATE	0.005	-0.152	-0.032	-0.325	-80.863	-69.330
	(0.055)	(0.194)	(0.043)	(0.284)	(143.632)	(69.910)
Sharpened-q	1	1	1	1	1	1
Control Mean	1.338	3.349	1.15	4.819	1592.48	625.37
[Std dev]	[1.272]	[4.898]	[1.124]	[7.205]	[4284.89]	[1537.49]
Observations	22,236	22,236	22,236	22,236	22,236	22,236

Notes: This table presents the main estimates for shopping behavior. Column 1 to 4 are count measures. Dietary diversity is measured as the unique number of food products (and drinks) purchased. ITT row reports the intention-to-treat (equation 1) and LATE row reports the local average treatment effect (equation 2) estimates, respectively. Both regressions include individual and week-in-panel fixed effects. Standard errors are clustered at the individual level. Last row reports the sharpened-q values for multiple hypotheses correction. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.10: Examining the Differential Impact of Having Access to the Government Subsidies

	Rice	Wheat	Legumes and other grains	Spices	Accompaniments	Snacks	Ready to eat	Nuts	Soft Drinks
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment	-0.298**	-0.016	0.053	0.069	0.023***	-0.117**	-0.009**	-0.078**	-0.098*
	(0.128)	(0.077)	(0.140)	(0.054)	(0.007)	(0.055)	(0.004)	(0.038)	(0.052)
Treatment × PDS Access	0.082	0.044	0.013	0.062	-0.016**	0.068	0.003	0.017	0.043
	(0.146)	(0.070)	(0.132)	(0.068)	(0.007)	(0.059)	(0.005)	(0.043)	(0.058)
Observations	22,236	22,236	22,236	22,236	22,236	22,236	22,236	22,236	22,236

Notes: This table presents the intent-to-treat estimates for weekly food expenditure on groceries. We use the full sample and add a separate control for accessing to government food subsidies interacted with treatment indicator. Outcomes are at the person-week level and reported here in levels (US$ PPP). Both regressions include individual and week-in-panel fixed effects. Standard errors are clustered at the individual level. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.11: Grocery Expenditure at the household level

	Rice	Wheat	Legumes and other grains	Spices	Accompaniments	Snacks	Ready to eat	Nuts	Soft Drinks
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ITT	-0.195**	0.053	0.097	0.109**	0.013***	-0.059	-0.008*	-0.077***	-0.057
	(0.099)	(0.050)	(0.152)	(0.045)	(0.004)	(0.039)	(0.005)	(0.029)	(0.039)
Observations	19,891	19,891	19,891	19,891	19,891	19,891	19,891	19,891	19,891

Notes: This table presents the intent-to-treat estimates for weekly food expenditure on groceries at the household level. Outcomes are at the household-week level and reported here in levels (US$ PPP). Note that the sample size is not identical to the individual-level analysis due to some participants belonging to the same household. Both regressions include individual and week-in-panel fixed effects. Standard errors are clustered at the individual level. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.12: Effect of Food Subsidies on Household-level Nutritional Purchases

	Calories	Protein	Fat	Carbohydrates	Sugar	Iron	Calcium	Zinc
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ITT	2,187.833	4.478	51.083	-5.823	-5.530	20.387*	174.989	0.305
	(1,872.691)	(14.659)	(38.476)	(91.803)	(20.856)	(11.531)	(261.013)	(0.523)
Observations	19,891	19,891	19,891	19,891	19,891	19,891	19,891	19,891

Notes: This table presents the main intent-to-treat estimates for nutritional purchases at the household level. Outcomes are at the household-week level and reported here in levels. Note that the sample size is not identical to the individual-level analysis due to some participants belonging to the same household. Calories are measured in kcal, macro nutrients (columns 2 to 5) measured in grams, and micro nutrients (colummns 6 to 8) measured in micro grams. Both regressions include individual and week-in-panel fixed effects. Standard errors are clustered at the individual level. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.13: Effects of the Experiment on Market Prices

	Unit Price (1)	Unit Price (2)	Unit Price (3)	Unit Price (4)
Experiment Start	0.00258	0.00258		
	(0.00365)	(0.00365)		
Rice or Wheat × Experiment Start			-0.00195	-3.043
			(0.00390)	(2.736)
Observations	185,550	185,550	185,550	185,550
Product Code Fixed Effect	Yes	Yes	Yes	Yes
Calendar Week Fixed Effect			Yes	Yes
Store Fixed Effect		Yes		Yes

Notes: This table presents the estimates for the start of of the experiment on market prices. The unit of analysis is a product week. Here we study products at the line-item level, identified by a unique product barcode (for loose items study coordinator assigns a unique id). We use no data from the post-experiment period. The outcome variable is the price per unit quantity (US$ at PPP per grams or milliliters). In columns 1 and 2 we estimate the changes in market prices after the starting of the experiment, using the following linear regression model: $Price_{pst} = \beta_0 + \beta_1 Post_t + \gamma_p + \delta_s + \varepsilon_{pst}$, where $Price_{pst}$ is the price of the SKU-level product p on store s, in week t. $Post_t$ is a binary variable indicating the start of the experiment and γ_p is the product fixed effect. We add the store fixed effect $delta_s$, in column 2. The coefficient of interest β_1, reflects the SKU-level products' price changes during the experiment period, compared to the pre-experiment period. In columns 3 and 4 we take all products (food and non-food items) that are not subsidized in the experiment as a control benchmark, and estimated the differential impact of start of the experiment on prices of rice and wheat. We use the following reduced-form regression model: $Price_{pst} = \alpha_0 + \alpha_1 Subsidized\ Good_p \times Post_t + \gamma_p + \delta_s + \epsilon_t + \varepsilon_{pst}$. Here we interact $Post_t$ with $Subsidized\ Good_p$, the binary variable indicating whether the product falls under rice or wheat category, and we add the week fixed effects ϵ_t. Coefficient of interest α_1 presents the differential impact of the start of the experiment on rice and wheat prices, the subsidized products, relative to all other products. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.14: Grocery Expenditure: Examining Potential Stockpiling

	Rice (1)	Wheat (2)	Legumes and other grains (3)	Spices (4)	Accompaniments (5)	Snacks (6)	Ready to eat (7)	Nuts (8)	Soft Drinks (9)
Treatment × Post	0.104	-0.069	0.079	0.101**	0.001	-0.016	-0.007	-0.040	-0.060
	(0.139)	(0.071)	(0.132)	(0.048)	(0.003)	(0.041)	(0.005)	(0.032)	(0.040)
Observations	17,204	17,204	17,204	17,204	17,204	17,204	17,204	17,204	17,204

Notes: This table presents the intent-to-treat estimates for weekly food expenditure on groceries. Outcomes are at the individual-week level and reported here in levels (US$ PPP). Note that the sample size is not identical to the main model in Table 3 since we drop the data from 6-week subsidy period, and instead used 2-week post subsidy period data. Both regressions include individual and week-in-panel fixed effects. Standard errors are clustered at the individual level. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.15: Forward-looking Behavior in the Control Arm

	Rice	Wheat	Legumes and other grains	Spices	Accompaniments	Snacks	Ready to eat	Nuts	Soft Drinks
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Enrollment	0.020	-0.142	0.171	0.021	-0.009	-0.054	0.004	0.029	-0.145
	(0.153)	(0.091)	(0.158)	(0.056)	(0.013)	(0.052)	(0.004)	(0.039)	(0.090)
Observations	8,774	8,774	8,774	8,774	8,774	8,774	8,774	8,774	8,774

Notes: This table presents the intent-to-treat estimates of being recruited to the control arm on the weekly food expenditures. Individuals that are later recruited to the study serves as a control benchmark. Outcomes are at the individual-week level and reported here in levels (US$ PPP). Note that the sample size is not identical to the main model in Table 3 since we only use data from the control arm individuals. Regressions include individual fixed effects along with a date fixed effects indicating the starting day of each week-in-panel. Standard errors are clustered at the individual level. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.16: Alternative Specifications

	Rice	Wheat	Legumes and other grains	Spices	Accompaniments	Snacks	Ready to eat	Nuts	Soft Drinks
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A. No Controls									
ITT	-0.301***	-0.055	-0.216	0.055	0.009***	-0.100**	-0.006**	-0.050**	-0.016
	(0.082)	(0.048)	(0.259)	(0.053)	(0.003)	(0.041)	(0.003)	(0.024)	(0.026)
Panel B. Time Fixed Effects									
ITT	-0.298***	-0.056	-0.222	0.055	0.009***	-0.101**	-0.006**	-0.053**	-0.017
	(0.083)	(0.048)	(0.278)	(0.054)	(0.003)	(0.041)	(0.003)	(0.026)	(0.026)
Panel C. Double Lasso Variable Selection									
ITT	-0.317***	-0.062	-0.141	0.054	0.009***	-0.091**	-0.006*	-0.050**	-0.007
	(0.085)	(0.050)	(0.238)	(0.055)	(0.003)	(0.041)	(0.003)	(0.024)	(0.027)
Observations	7,548	7,548	7,548	7,548	7,548	7,548	7,548	7,548	7,548

Notes: This table presents the intent-to-treat estimates for weekly food expenditure on groceries. Outcomes are at the individual-week level and reported here in levels (US$ PPP). Here we only use data from the experiment period. In Panel A, we estimate a linear regression in the following form: $Y_{it} = \alpha TREAT_i + \zeta_{it}$. Panel B includes time fixed effects indicating the first date of each week-in-panel. Panel C presents regression estimates with control variables that are selected using a double LASSO (Belloni, Chernozhukov and Hansen, 2014) (we consider the set of potential variables presented in the Balance Table A.1. Standard errors are clustered at the individual level. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.17: Alternative Outcome Variables

	Rice	Wheat	Legumes and other grains	Spices	Accompaniments	Snacks	Ready to eat	Nuts	Soft Drinks
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A. Expenditure: Log Transform									
ITT	-0.026*	0.008	0.004	0.025*	0.006***	-0.026*	-0.003*	-0.012**	-0.026**
	(0.015)	(0.011)	(0.021)	(0.014)	(0.002)	(0.014)	(0.002)	(0.005)	(0.011)
Panel B. Expenditure: Alternative Error Clustering Structure									
ITT	-0.245**	0.013	0.062	0.109**	0.013***	-0.074*	-0.007	-0.067**	-0.071**
	(0.096)	(0.047)	(0.115)	(0.044)	(0.004)	(0.036)	(0.005)	(0.029)	(0.033)
Panel C. Number of Shopping Trips									
ITT	-0.023	0.006	-0.070	0.074	0.009**	-0.090	-0.003	-0.013**	-0.006
	(0.016)	(0.009)	(0.055)	(0.057)	(0.004)	(0.073)	(0.004)	(0.006)	(0.035)
Panel D. Variety Purchased									
ITT	-0.023	0.006	-0.067	0.072	0.009**	-0.089	-0.003	-0.013**	-0.070*
	(0.016)	(0.009)	(0.054)	(0.056)	(0.004)	(0.073)	(0.004)	(0.006)	(0.040)
Observations	22,236	22,236	22,236	22,236	22,236	22,236	22,236	22,236	22,236

Notes: This table presents the intent-to-treat estimates for weekly food expenditure on groceries. Outcomes are at the individual-week level. In Panel A dependent variables are the natural log transformation of 1 plus the outcome of interest (in expenditure). In Panel B, the two-way standard errors are clustered at the participant and week-in-panel level. Panel C presents the estimates on the number of shopping trips that include the focal product. Panel D presents the variety (measured as the unique number of SKUs) purchased in the focal product. Regressions include individual and week-in-panel fixed effects. Standard errors are clustered at the individual level. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.18: Grocery Expenditure Robustness: Adding Calendar Week Fixed Effects

	Rice	Wheat	Legumes and other grains	Spices	Accompaniments	Snacks	Ready to eat	Nuts	Soft Drinks
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ITT	-0.244***	0.013	0.064	0.109***	0.013***	-0.074**	-0.007*	-0.068**	-0.070**
	(0.091)	(0.052)	(0.124)	(0.042)	(0.003)	(0.037)	(0.004)	(0.027)	(0.033)
Observations	22,236	22,236	22,236	22,236	22,236	22,236	22,236	22,236	22,236

Notes: This table presents the intent-to-treat estimates for weekly food expenditure on groceries. Outcomes are at the individual-week level and reported here in levels (US$ PPP). Here we include calendar week fixed effects in addition to the individual and week-in-panel fixed effects to the model defined in equation 1. We take the start date of each week-in-panel to define the calendar week. Standard errors are clustered at the individual level. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.19: Nutritional Purchases Robustness: Adding Calendar Week Fixed Effects

	Calories (1)	Protein (2)	Fat (3)	Carbohydrates (4)	Sugar (5)	Iron (6)	Calcium (7)	Zinc (8)
ITT	1,736.450	-5.296	42.883	-67.841	-18.801	17.414*	133.483	0.209
	(1,643.039)	(12.839)	(34.042)	(81.624)	(17.949)	(10.280)	(239.066)	(0.522)
Observations	22,236	22,236	22,236	22,236	22,236	22,236	22,236	22,236

Notes: This table presents the main intent-to-treat estimates for nutritional purchases. Outcomes are reported here in levels. Here we include calendar week fixed effects in addition to the individual and week-in-panel fixed effects to the model defined in equation 1. We take the start date of each week-in-panel to define the calendar week. Calories are measured in kcal, macro nutrients (columns 2 to 5) measured in grams, and micro nutrients (columms 6 to 8) measured in micro grams. Standard errors are clustered at the individual level. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.20: Heterogeneity Robustness: Adding Calendar Week Fixed Effects

Panel A. Parental Status							
	No Children				One Child or More		
	Rice (1)	Snacks (2)	Spices (3)		Rice (4)	Snacks (5)	Spices (6)
ITT	-0.134	-0.018	0.163**	-0.293***	-0.095**	0.089*	
	(0.170)	(0.047)	(0.074)	(0.108)	(0.047)	(0.051)	
Control Mean	0.596	0.256	0.301		0.701	0.469	0.350
Observations	6,357	6,357	6,357		15,879	15,879	15,879
Panel B. Household Income							
	Below Median Income				Above Median Income		
	Rice (1)	Snacks (2)	Spices (3)		Rice (4)	Snacks (5)	Spices (6)
ITT	-0.304**	-0.163***	0.174**	-0.151	0.005	0.041	
	(0.145)	(0.059)	(0.070)	(0.106)	(0.042)	(0.046)	
Control Mean	0.623	0.363	0.323		0.726	0.459	0.352
Observations	11,033	11,033	11,033		11,203	11,203	11,203
Panel C. Past Purchasing Behavior							
	No Purchase				At Least One Purchase		
	Rice (1)	Snacks (2)	Spices (3)		Rice (4)	Snacks (5)	Spices (6)
ITT	-0.055	-0.010	-0.009	-0.591***	-0.087**	0.157***	
	(0.035)	(0.020)	(0.013)	(0.196)	(0.044)	(0.059)	
Control Mean	0.047	0.021	0.02		1.31	0.495	0.45
Observations	11,828	3,948	6,189		10,408	18,288	16,046

Notes: Outcomes are at the person-week level and reported here in levels (US$ PPP). Here we include calendar week fixed effects in addition to the individual and week-in-panel fixed effects to the model defined in equation 1. We take the start date of each week-in-panel to define the calendar week. ITT reports the intent-to-treat estimates. Standard errors are clustered at the individual level. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.21: Comparing Basket Characteristics of Experiment Sample with Others

	Money Spent	Quantity Purchased	Calories	Protein	Carbohydrates	Fat
	(1)	(2)	(3)	(4)	(5)	(6)
Experiment Sample	-1.382	14.327	549.914	2.481	16.815	3.064
	(1.654)	(24.127)	(367.141)	(3.212)	(22.885)	(7.99)
Constant	34.217***	627.234***	3050.32***	33.416***	202.688***	89.355***
	(1.180)	(37.877)	(206.472)	(2.116)	(14.285)	(5.073)
Observations	50,468	50,468	50,468	50,468	50,468	50,468

Notes: This model presents the estimates for comparing the experiment sample with other tagged shoppers on basket-level data. Here we restrict our attention to data collected prior to July 1, 2022, the date in which the sample to invite to the experiment is determined. Column 1 is in US$ PPP, Column 2, 4, 5, and 6 are in grams. Column 3 is in calories. Standard errors are clustered at the individual level. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.22: Secondary Heterogeneity Analysis

Panel A. Parents' Employment						
	Not Working Parent			Employed Parent		
	Rice	Snacks	Spices	Rice	Snacks	Spices
	(1)	(2)	(3)	(4)	(5)	(6)
ITT	-0.627***	-0.012	0.120	-0.092	-0.143**	0.073
	(0.191)	(0.072)	(0.088)	(0.130)	(0.063)	(0.061)
Control Mean	0.545	0.549	0.356	0.793	0.421	0.347
Observations	5,889	5,889	5,889	9,990	9,990	9,990
Panel B. Controlling for Gender						
	Not Working Parent			Employed Parent		
	Rice	Snacks	Spices	Rice	Snacks	Spices
	(1)	(2)	(3)	(4)	(5)	(6)
ITT	-1.245*	-0.080	0.015	-0.105	-0.164**	0.082
	(0.641)	(0.085)	(0.102)	(0.140)	(0.067)	(0.066)
ITT × Female	0.715	0.078	0.121	0.090	0.147	-0.062
	(0.644)	(0.081)	(0.133)	(0.171)	(0.106)	(0.129)
Observations	5,889	5,889	5,889	9,990	9,990	9,990

Notes: Outcomes are at the person-week level and reported here in levels (US$ PPP). All regressions include individual and week-in-panel fixed effects. ITT reports the intent-to-treat estimates. Standard errors are clustered at the individual level. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.23: Subsidy take-up and grocery purchase rates

	Grocery Purchase Rate (%) (1)	Subsidy Take-up rate (%) (2)	Protein value of the subsidy (grams) (3)	Average protein take-up (grams) (4)	Average protein purchases in groceries (grams) (5)
Rice	7.99	62.76	158.8	99.67	112.58
	(0.82)	(15.59)		(24.76)	(10.96)
Wheat	4.26	61.96	254.75	157.85	83.14
	(6.70)	(11.54)		(29.42)	(9.88)
Lentils	15.72	56.77	325	184.51	94.62
	(1.31)	(9.45)		(30.71)	(8.98)
Millet	0.55	44.57	333.59	148.69	115.57
	(0.19)	(12.32)		(41.1)	(15.82)

Notes: This tables presents grocery purchasing and subsidy take-up rates for four product categories, along with the protein values of each subsidy. The sample consists of 748 individuals, who were in the control arm of the experiment and randomly assigned to one of four food subsidy programs two week after the experiment. Post-experiment subsidy programs take four weeks. Column 1 presents the grocery purchase rate of each category prior to the post-experiment subsidies. Column 2 presents the subsidy take-up rates. In column 1, for each product category, we restrict the sample to those who receive the same product as a subsidy later on, to maintain fair comparison. Column 3 present the protein value of each food subsidy program in grams. Column 4 presents the multiplication of columns 2 and 3, namely, the average grams of protein take-up. Column 5 presents the average protein purchases of each trial arm during the 4-week subsidy period. In columns 1 and 2 outcomes are at the percentage level, and in columns 3, 4, and 5 outcomes are measured in grams. In columns 1, 2, 4, and 5, we use two-way clustered standard errors at the individual and week level.